A composite index-based insurance instrument for managing the financial risk of variable hydrometeorology for electric utilities

Yash Amonkar[a,b], Corey Pahel-Short[a,b], Amir Zeighami[c], Yufei Su[e], Jordan D. Kern[c,d], and Gregory W. Characklis[a,b]

[a]*Institute for Risk Management & Insurance Innovation (IRMII), University of North Carolina at Chapel Hill, Chapel Hill, NC, USA.*

[b]*Department of Environmental Sciences and Engineering, Gillings School of Global Public Health, University of North Carolina at Chapel Hill, Chapel Hill, NC, USA.*

[c]*Department of Forestry and Environmental Resources, North Carolina State University, Raleigh, NC, USA.*

[d]*Department of Industrial and Systems Engineering, North Carolina State University, NC, USA.*

[e]*S&P Global, Commodity Insights, Shanghai, China.*

Note - This paper is a non-peer-reviewed preprint submitted to EarthArXiv and is currently under consideration for peer review.

Abstract

Variable hydrometeorological conditions can impact electric utilities' financial stability. Extreme temperatures often increase electricity demand, raising utility costs, while drought reduces hydropower generation and often reduces revenues, with financial impacts potentially exacerbated by spikes in fuel prices, particularly natural gas. In this study, a model of the U.S. West Coast power system is combined with a financial risk model of a large California electric utility as it responds to variable hydrometeorology and market conditions, and is used to test the performance of a novel financial tool for managing risk. An insurance contract based on a composite index of measures related to streamflow, temperature, and natural gas prices is developed and its cost-effectiveness is compared against a portfolio of three currently available index contracts each based on a single index. The new composite index contract achieves an equivalent reduction in the utility's net revenue variance as a portfolio of the three existing contract types for roughly half the cost with the cost reduction largely attributable to lower basis risk associated with the composite index contract. The utility's financial risk and the effectiveness of the new contract are also explored under an alternative regulatory scenario involving a pollution tax intended to reduce air pollution damages and emissions. Overall, this case study represents a new approach to managing financial risk arising from hydrometeorological and market variability for vertically integrated utilities, the most common utility structure.

Article Keywords - Electric Utilities, Index Insurance, Financial Risk Management, Hydrometeorological Variability, Energy Markets, CAISO

1 Introduction

Variable hydrometeorological conditions, particularly in the form of drought and extreme temperatures, expose electric utilities to financial risk in the form of intermittent reductions in generation and increases in electricity demand, which combine to force greater reliance on more expensive generation [Bates et al., 2008, McMahan and Gerlak, 2020, Gleick, 2017]. For example, electric utilities with significant hydropower assets experience decreased generation due to reduced reservoir inflows during drought [Bates et al., 2008, Blomfield and Plummer, 2014]. Deviations from expected temperatures, such as cooler than expected summers or warmer winters, can also substantially reduce revenues based on electricity demand, the majority of which is driven by the heating and cooling of buildings [Comstock, 2018, Serzan, 2019]. Similarly, extremely high or low temperatures lead to large spikes in demand that a utility must often meet via the use of more expensive, generation or reliance on market purchases during high price periods. As these fluctuations are related to weather, both their intermittent nature and unpredictable severity present utilities with financial uncertainty.

Further exacerbating these challenges is the often correlated nature of droughts and heat waves, raising the probability that periods of low electricity supply and high demand will occur simultaneously [AghaKouchak et al., 2014]. This combination of environmental events can force electric utilities to fall back on alternative generation sources that are not only much more expensive, but also significantly more polluting, as is the case in California and even in other grids, where older, less efficient thermal generation is used as a last resort (Figure S1).

California's electric utilities have recently experienced acute financial impacts from variable hydrometeorology [DiSavino, 2021]. During California's 2012-2016 drought, high temperatures led to increased electricity demand necessitating reliance on more expensive power sources, which cost the state's three largest investor-owned utilities an additional $3.8 billion, while lost hydropower generation accounted for another $1.9 billion in losses [Kern et al., 2020]. The increased use of thermal power during these hydrometeorological extremes also had an impact on public health in California, as these more expensive sources are also more polluting and increase air pollutant emissions, raising questions about how these spikes in emissions could be reduced [Gleick, 2017, Herrera-Estrada et al., 2018].

While extreme weather events pose many operational challenges for electric utilities in terms of supply reliability, there is also growing attention to the financial risks associated with the attendant intermittent swings in costs and revenues [Allianz SE, 2013]. Traditional financial risk management tools, such as reserve funds and lines of credit, often prove effective for managing more moderate hydro-meteorological fluctuations, but the growing frequency and severity of these events has utilities searching for more innovative tools and strategies [Larson et al., 2012, Meenan et al., 2019]. This has resulted in greater interest in financial risk transfer instruments, such as index-based insurance, which has been shown to be effective at managing the financial consequences of more extreme events and has even been shown to increase the market value of electric and gas utilities with weather-related exposure [Pérez-González and Yun, 2013]. Utilities exposed to significant financial risk by hydrometeorological events are being increasingly scrutinized by investors, lenders, and credit rating agencies [Moody's, 2013] as such risk can lead to higher interest rates on borrowing, a critical consideration in the capital intensive electric power sector.

Financial contracts in the form of options, forwards or futures are commonly used in the electric power sector to protect against fluctuations in commodity prices (e.g., natural gas, crude oil, wholesale electricity) [Burger et al., 2014, Schofield, 2021]. These contracts typically obligate a buyer to purchase or sell a commodity on an agreed upon amount in the future at a predetermined price [Deng and Oren, 2006, Hull, 2022]. In recent years, index-based insurance contracts have been developed that facilitate payouts to the contract buyer from a "counterparty" (often an insurer or financial institution) when a specified threshold is crossed on a defined index that serves as a proxy for a financial metric of concern (e.g., costs, revenues). These types of contracts are often used to manage the financial risk of deviations from established hydrometeorological patterns, such as low precipitation [Larson et al., 2012] or extreme temperatures. These contracts differ from traditional indemnity-based insurance, in which payouts rely on an onsite determination of damages made after a covered loss occurs (e.g., floods). Index-based insurance can offer a useful alternative by removing the subjective human element in determining loss while also accelerating the time to payout, which can sometimes be quite lengthy in the case of indemnity-based contracts [Meenan et al., 2019]. For example, temperature-based index contracts are used by electric utilities to manage the unexpected reductions in demand and the lower revenues that accompany cooler summers and warmer winters [Artemis, 2022]. Index-based contracts are also commonly applied in agriculture to protect farmers against the financial ramifications of weather-related crop losses (e.g., drought, extreme temperatures) [Turvey, 2001]. One potential drawback to index-based contracts, however, is basis risk, which results when there is poor correlation between the specified index and financial losses. High basis risk leads to over- or under-payment relative to the losses, making the instrument ineffective and/or expensive. Developing an effective index-based contract requires maintaining a low level of basis risk by ensuring the index and losses are strongly correlated [Clement et al., 2018, Woodard and Garcia, 2007].

Electric utilities are well-acquainted with the concept of index-based contracts as risk management tools, having long used temperature-based derivative contracts, as well as those linked to natural gas prices, to manage the related financial risks. Index-based contracts have more recently also been employed to manage drought-related financial losses for hydropower producers [Blomfield and Plummer, 2014, The World Bank, 2018], with several recent studies pointing to the potential for more innovation in this area [Foster et al., 2015, Kern et al., 2015, Hamilton et al., 2020, Denaro et al., 2018]. Most electricity producers rely on more than just hydropower; however, their net revenues are influenced by multiple factors, such that their financial risk management requires consideration of more than just a single measure. In this case, financial risk management is often approached by using a portfolio of available single index contracts, which might include contracts that are separately intended to manage risks related to variations in temperature, hydrology, and market prices, but more recent research suggests that a "composite" contract based on a multivariate index could be useful [Kern et al., 2015, Li et al., 2021, Murthy et al., 2022, Shi and Jiang, 2016]. Kern et al. [2015] used a composite index that incorporated consideration of both hydrologic conditions and natural gas prices, which often correlate well with wholesale electricity prices in markets where the marginal generators use natural gas, to lower the basis risk of a contract designed to provide risk management for a hydropower-only generator selling power into an electricity market. More sophisticated multi-variate composite indices have also been explored in the agricultural sector [Li et al., 2021, Murthy et al., 2022]. Shi and Jiang [2016] demonstrated that a composite index-based contract could effectively protect farmers against multiple weather hazards (e.g., rainfall, temperature) that influence rice yields and suggested it should be less expensive than a portfolio of single index contracts, but did not explore the question further. Given the multiple weather hazards and market uncertainty facing electric utilities with many sources of generation, a composite index-based contract might be developed as a means of more cost-effectively managing multiple risks.

Developing risk management tools for electric utilities with a diverse generation mix complicates the relationship between drought and revenue loss relative to that of a hydropower producer by itself. A composite index insurance contract that simultaneously accounts for the risk of compounding hydrometeorological extremes (e.g., temperature, and drought) could increase the correlation between the index and a utility's costs and revenues (or considered together, net revenues), thus lowering basis risk and improving the instrument's performance. To explore this idea, a composite index insurance contract that considers hydrologic conditions, temperature and wholesale natural gas prices is developed in this study. The performance of the composite index contract and a portfolio of existing single-index contracts that independently address the same three risks is compared in terms of cost and effectiveness.

These two approaches are evaluated using the situation faced by Pacific Gas and Electric Company (PG&E), a publicly traded utility in California that earns revenues through the generation, sales, and transmission of electricity. Pacific Gas & Electric is vulnerable to extreme temperatures and high natural gas prices in addition to drought [Kern et al., 2020], such that a composite index considering multiple metrics related to these factors may lead to higher levels of agreement between the index and PG&E's net revenues, in large part due to its consideration of cross-correlation between these three factors. This should lower basis risk and result in a more effective risk management instrument, particularly as it will better account for the financial impacts of compound risks involving the incidence of both drought and heatwaves, which are often correlated in many parts of the world [Mukherjee et al., 2020, Zscheischler et al., 2018, Kong et al., 2020]. While this analysis is applied to PG&E, the new financial instrument could be useful for any electric utility with concerns over how variability in hydrometeorological and market conditions will affect its operations and finances.

Alternative Regulatory Scenario

Air pollution emissions from power plants impact public health, and these emissions tend to increase when conventional thermal generation is increased to meet electricity demand, as more expensive sources, which are also often more polluting, come online. Proposals to limit pollution damages and emissions by using taxes on the pollutants of concern are intended to encourage the adoption of new, less polluting technologies and have become increasingly common [C2ES, 2022]. If pollution taxes on power plants were imposed in California, it is likely to incentivize PG&E to use generators that produce less pollution before dispatching its higher polluting generators, thereby changing its generation dispatch to lower emissions and presumably improving public health.

Even with the advent of a pollution tax, the utility would still need to dispatch its most polluting generators during periods of extraordinarily high electricity demand, especially if high demand occurs during periods of decreased hydropower supply (e.g., during drought and/or late summer), as the alternative would be blackouts (i.e. when demand for electricity exceeds supply) [Nguyen, 2020]. Consequently, during such extreme hydrometeorological conditions, the pollution tax would impose greater costs on PG&E at times when it is financially vulnerable, and thus the tax would exacerbate its financial risk. Overall, the same hydrometeorological conditions that give rise to financial risk also give rise to increased air pollution [Zeighami et al., 2023]. Therefore, the composite index-based instrument is also evaluated under a scenario involving a pollution tax implemented across California to determine the degree to which it can reduce financial risk in such situations, and thereby remove some of the disincentives for implementing a tax intended to improve public health. Implementing a financial instrument to better manage the heightened financial risk that would accompany the pollution tax on PG&E during periods of extreme hydrometeorology could, therefore, ease the utility's transition to a generation mix that leads to improved public health.

2 Methods

Figure 1 represents the overall modeling framework used in this study. This study uses the outputs from a unit commitment & economic dispatch model of the American West (California and West Coast Power Systems model (CAPOW)) run at an hourly time step using simulated weather and electricity market conditions. CAPOW's outputs, including generator dispatch and wholesale electricity prices are used in conjunction with a financial model of PG&E's business operations to produce estimates of PG&E's annual net revenues. These annual net revenues serve as targets for financial risk management using multiple strategies. A newly designed composite index-based contract is then compared against a portfolio of existing single-index contracts to determine the cost-effectiveness of each approach in managing PG&E's net revenue variability. The effectiveness of using the newly designed composite contract is also assessed under an alternative regulatory scenario, involving a pollution tax designed to reduce public exposure to pollutant emissions, a scenario in which PG&E's financial risk increases.

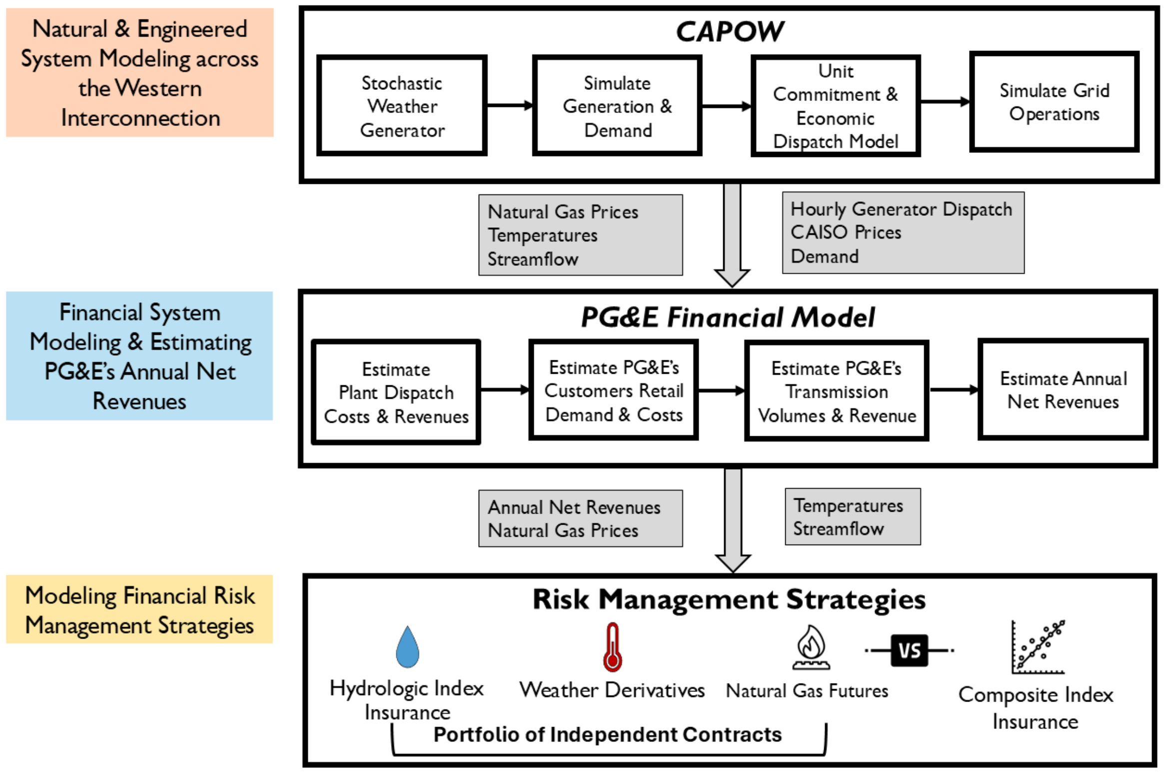

Figure 1: The overall manuscript modeling framework. The only difference between the baseline scenario and the alternative regulatory scenario with a pollution tax is changes in generation costs for thermal power plants, which serve as inputs to the unit commitment and economic dispatch model within CAPOW.

2.1 Study Region

Pacific Gas & Electric provides electricity services for much of northern and central California (Figure 2). Most of PG&E's business focuses on the generation, transmission, and delivery of electricity, and these parts of its business are the focus of this analysis. As of 2018-2020, the utility's primary electricity generation sources include nuclear (2,240 MW), conventional hydropower (2,655 MW), pumped storage hydropower (1,121 MW), natural gas plants (1,400 MW), solar photovoltaic (152 MW), and electricity sourced from third-party electricity generators, primarily renewable (e.g., solar, wind), through power purchase agreements (PPAs) [PG&E Corporation, 2018, 2019, 2020a].

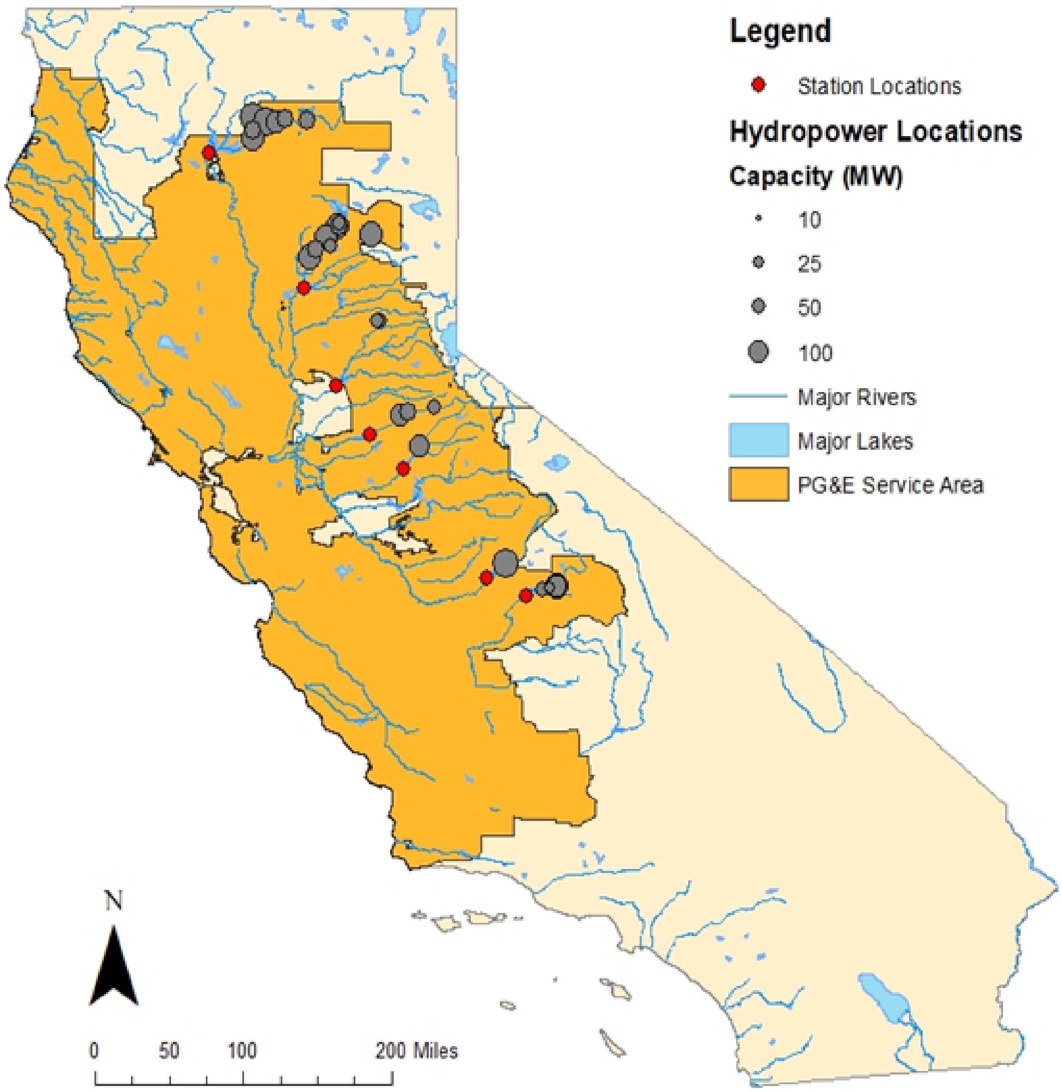

Figure 2: PG&E's service area in California, showing the locations of its hydropower capacity and the stream-level monitoring stations used in this work [California Energy Commission, 2021, California Natural Resources Agency, 2020, 2022].

Some of PG&E's vulnerability to hydrometeorological risk is due to its hydropower facilities, the majority of which are located at higher elevations in the Sierra Nevada Mountains [PG&E Corporation, 2022]. A significant portion of the state's precipitation occurs as snow in the Sierra Nevada, which results in the majority of annual streamflow coming in the spring and summer as snowmelt [Huning and Margulis, 2017, Serreze et al., 1999]. Variability in snowfall amounts and timing can negatively affect hydropower operations that have traditionally relied on snowpack as additional storage for high-altitude reservoirs, most of which have very limited storage capabilities [Aspen Environmental Group and M. Cubed, 2005]. In addition to decreasing hydropower generation, drought can threaten thermal generation through reduced access to cooling water, leading to a reduction in generation and revenues [van Vliet et al., 2012]. This is primarily a concern for "once-through" power plants, which use greater amounts of water, very few of which exist in California [Madden et al., 2013]. Thus, cooling water issues have not historically been a problem in the state and are not considered a significant risk to PG&E's operations.

Ambient air temperatures are also a key contributor to PG&E's financial risk. While PG&E generally benefits from periods of warmer weather and increased electricity demand, short-term temperature extremes caused by heat waves, especially during late summer when hydropower supply is low, have resulted in very high market prices for electricity (a problem for PG&E as it buys more electricity from the market than it sells during these periods) [Nguyen, 2020]. Additionally, an altered regulatory environment, including changes to tax policy, is named in the financial report as a risk that could impact PG&E's financial condition. This could include the enactment of pollution taxes on air emissions from power plants, which would increase the utility's costs. As the combination of drought (less hydropower supply) and heatwaves (increased demand) often force PG&E to bring its most expensive and dirtiest generation sources online, the tax would likely be imposed under the same type of hydrometeorological conditions that already create financial risk.

2.2 Modeling Framework

2.2.1 California and West Coast Power Systems Model (CAPOW)

The California and West Coast Power (CAPOW) Systems Model is a Python-based model that simulates the electrical power system and wholesale electricity markets across the West Coast region, including all of Washington, Oregon, and California [Su et al., 2020a]. The model includes the California Independent System Operator (CAISO) wholesale electricity market, in which PG&E participates in, along with the Mid-Columbia (Mid-C) wholesale electricity market, which covers most of the Pacific Northwest. It is important to model the entire system, as PG&E is influenced by conditions outside its service area. For example, drought in the Pacific Northwest (Mid-C) reduces hydropower generation and electricity exports to California, thereby impacting CAISO's generation mix and electricity prices.

The CAPOW model has two main components: a synthetic weather generator and a unit commitment and economic dispatch (UC/ED) model that determines when and how much electricity is generated at each source. Historical

West Coast hydrometeorological data, including streamflows and temperatures, are input to the weather generator, which then uses statistical relationships to produce daily synthetic hydrometeorological data that are statistically consistent with historical observations at each monitoring station, while also reproducing both temporal and spatial autocorrelation in different parameters across locations throughout the region [Su et al., 2020a]. This stochastic approach allows for the generation of extreme hydrometeorological events outside of the more limited historical record, allowing for financial risk management strategies to be analyzed under a broader range of conditions.

The UC/ED model uses the simulated hydrometeorological and grid conditions (hydropower and thermal generation, electricity demand, renewable availability) within a mixed-integer linear optimization to determine generator dispatch and the wholesale electricity price. This is done by simulating the dynamics of the CAISO electricity market by determining the generation mix that minimizes the costs of meeting electricity demand. Generators with the lowest marginal costs are dispatched first, with more expensive generators dispatched in order of increasing cost as demand rises. The highest marginal cost generator used to meet demand sets the market's wholesale electricity price [US EIA, 2012]. Outputs from the UC/ED model include hourly CAISO wholesale electricity prices ($/MWh) and hourly generator dispatch for the region. Running the UC/ED model using historical conditions produces wholesale prices that agree quite well with observed market prices, with an R^2 value of 0.75 [Su et al., 2020a]. For more details on CAPOW, including its validation and applications, see [Su et al., 2020a, Kern et al., 2020, Su et al., 2020b]. Variable stochastic natural gas prices are incorporated into CAPOW during a post-processing step. This is straightforward given that gas prices uniformly affect the marginal generation costs of natural gas plants, which dominate California's electricity generation and are essentially always the marginal producers that set market prices [Hodge, 2022] (i.e., the order of plant dispatch by the UC/ED is not impacted). For more information on incorporating variable natural gas prices into the modeled generation costs and wholesale electricity prices, see Supplementary Materials Note A.

Five hundred simulations each of duration one year were generated using the CAPOW modeling framework. The temporal resolution of each simulation was hourly leading to 8,760 time-steps. The next step included checks to ensure the spatial and temporal cross-correlations across the simulations represented the variability in the data. Across the 500 simulations, a single simulation displaying spurious correlations was removed. Given that the framework models the entire West Coast (Washington, Oregon and California including the entirety of CAISO), variables of interest for the PG&E domain were extracted. These include the CAISO hourly market price, demand, streamflow, hydropower generation, wind and solar power generation, and temperatures across the population centers within PG&E.

2.2.2 PG&E Financial Model

The generator dispatch schedule and wholesale electricity prices produced by CAPOW are used as inputs into the PG&E financial model, which describes the utility's business operations. These consist primarily of the following: (i) generating electricity via owned and procured assets (i.e., PPAs) to sell on CAISO's wholesale electricity market, (ii) making purchases from the wholesale electricity market to meet customer demands, and (iii) distributing electricity to consumers. Total electricity generation costs are calculated using the electricity generated (MWh) by each of PG&E's dispatched plants and the plants' corresponding marginal generation costs ($/MWh). The PPA contract prices for acquired electricity ($106.2/MWh for renewable generators and $33.15/MWh for conventional thermal generators) are estimated using cost and generation information from PG&E's financial report and sustainability report [PG&E Corporation, 2018, 2020b]. Pacific Gas and Electric sells this generated and procured electricity on the wholesale electricity market at the current wholesale price and then purchases electricity back to meet its retail customer demand. Retail customers are sorted into four general categories: residential, commercial, industrial, and agricultural. Retail electricity rates used in the model range from $0.10/kWh to $0.22/kWh, depending on both the customer type and time of year, with summer rates being higher than winter rates [PG&E Corporation, 2018]. Although electricity consumers in PG&E's service area can choose among different electricity providers in the region (e.g., through community choice aggregation programs), PG&E still owns much of the existing transmission infrastructure and charges a fee for any electricity delivered even if PG&E is not the generator.

The delivery charge used by the model was estimated using PG&E's publicly available rate information [PG&E Corporation, 2018]. Model output in the form of PG&E's revenues (i.e., from retail customers and transmission), its costs (i.e., from fuel purchases, PPAs, and net wholesale market purchases), and its hydropower generation are compared against observations of net revenues over the historical period, which range from \$12 - \$12.3 billion [PG&E Corporation, 2018]. Operations and maintenance (O&M) costs contribute a significant portion of revenue variability attributed to managing wildfire risk [PG&E Corporation, 2020a]. Since wildfire impacts are not included in this analysis and their impact cannot be isolated from recent O&M costs and overall additional charges, these costs are left out of the net revenue calculations. Therefore, it should be noted that the net revenues analyzed in this study for any given year would likely be shifted down by O&M costs of a similar magnitude.

In order to isolate the influence of hydrometeorological events on PG&E's net revenues, this work defines annual net revenues (NR) as the following:

$$NR(\$B) = Market_{rev} + Retail_{rev} + Transmission_{rev} - Market_{costs} - Fuel_{costs} - PPA_{costs} \tag{1}$$

where, $Market_{rev}$ are revenues from electricity sold on the wholesale market.

$Retail_{rev}$ are revenues from retail customers. $Transmission_{rev}$ are revenues from electricity transmission. $Market_{costs}$ are costs of electricity purchased from the wholesale market. $Fuel_{costs}$ are power plant fuel costs. PPA_{costs} are costs associated with PPAs. All of these variables are impacted by hydrometeorological conditions, which in turn affect the supply and demand of electricity.

2.3 Managing Financial Risk using Index Based Instruments

Index Insurance Contract Design Considerations

In developing a new index-based financial instrument to manage risk, a primary objective is identifying an index that can accurately characterize PG&E's financial risk due to variable hydrometeorology. Daily streamflows at PG&E's major dams in the Sierra Nevada (which are widespread and thus a useful indicator, see Figure 2) are used to determine if the region is experiencing a dry year, and therefore, decreased hydropower generation. The locations of PG&E's major hydropower dams are mapped, and, using the dams' capacities, the percentage of PG&E's hydropower that corresponds to each streamflow station is identified (Figure 2). Streamflows at each station are weighted during aggregation to represent the proportion of corresponding hydropower generating capacity located at each facility, with the aggregate value representing the hydrologic index. Cooling degree days (CDD) are used to develop proxy relationships for electricity demand during the summer as electricity demand is highly correlated with ambient air temperatures [Hull, 2022, DeVilbiss and Morey, 2021]. These can be aggregated over a specified period (e.g., season, year) to get an understanding of that period's electricity demand for cooling and any deviations from expected demand and revenues that might occur. Using temperatures generated by CAPOW for major cities (Fresno, Sacramento, San Francisco and San Jose) within PG&E's service region, annual CDD is computed for each city as:

$$\sum_{i=1}^{365} \max(T_i - 65, 0) \tag{2}$$

where, T_i is the average daily temperature in Fahrenheit. It is assumed that 65 F is the ambient air temperature at which little heating or air conditioning is needed to maintain a comfortable building temperature with demand for electricity used for cooling buildings rising linearly at temperatures above that point [Mathews, 2009]. In order to represent the total regional electricity demand during the summer, CDD values are calculated for each city and then aggregated.

An important consideration during contract design is whether the contract buyer or seller has a reasonable ability to predict and/or manipulate the index and thus the contract outcome. Neither party should have an advantage in terms of predictive power, such that they have better information regarding the probability of payouts being made. While predictive power over summer temperatures and the average annual wholesale electricity price is already limited to very short periods (e.g., days to weeks), spring and summer streamflows in the Sierra Nevada Mountains can be predicted using the preceding winter snowfall amounts. Index contracts based on annual streamflows in this area are, therefore, written before

October 1st (beginning of the Water Year) as there is limited snowfall forecasting ability before this date [Kapnick et al., 2018, Shukla and Lettenmaier, 2011].

With respect to streamflow, an ideal index would in many cases use measurements taken upstream of PG&E's dams. In this case, flow data are available only downstream of the dams, offering the possibility that the utility might be able to manipulate the hydrologic component of the index. However, the high-altitude reservoirs that are the source of PG&E's hydropower are relatively small and have very little interannual storage capability [Aspen Environmental Group and M. Cubed, 2005], meaning PG&E must effectively allow all the water flowing into its hydropower reservoirs in a given year to flow out in the same year, ensuring no influence of antecedent storage conditions on the probability of payout. The contract is thus structured so that the streamflow component of the index is a function of annual flows thereby reducing concerns over PG&E's ability to effect the final value. With respect to the use of natural gas prices, there is little ability for PG&E to manipulate these as the primary drivers of changes in these prices are global in nature and independent of drought and temperature [Su et al., 2020b]. This, along with the use of temperatures at gauges managed by government agencies, should prevent PG&E from exercising any influence over any component of the proposed composite index or individual indices.

Index Insurance Contract Structure and Pricing

Index-based insurance contracts are typically designed to trigger a payout once the index drops below, or rises above, a predetermined threshold or a "strike". Figure 3 depicts the generalized structure of an index-based insurance contract. In that case, the strike is set at the 15th percentile of the index (i.e., approximately 15th percentile net revenues), such that payouts are triggered when the index drops below this level. It is assumed that net revenue losses up to this point are managed via other means (e.g., reserve fund, lines of credit), with greater losses considered "unmanaged" if the index contract not in place. This is consistent with practice, as index-based insurance and other types of risk transfer contracts are typically used to protect against extreme risks that occur once every 10 years or less [Meenan et al., 2019]. The selected strike in Figure 3 results in positive net payouts (years with payouts that are greater than the annual premium) slightly less than 15% of the time (intersection of the horizontal dotted line with the solid blue line). Lowering the strike to cover only the most extreme events (e.g., to the 10th percentile) would result in less frequent net payouts. While the selected levels of protection provided by the index-based insurance (i.e. one year in 10 or one year in 5) are roughly consistent with practice, the actual choice of a strike depends on both the level of financial protection the buyer maintains in other forms, such as a reserve and/or access to credit, as well as the buyer's level of risk aversion.

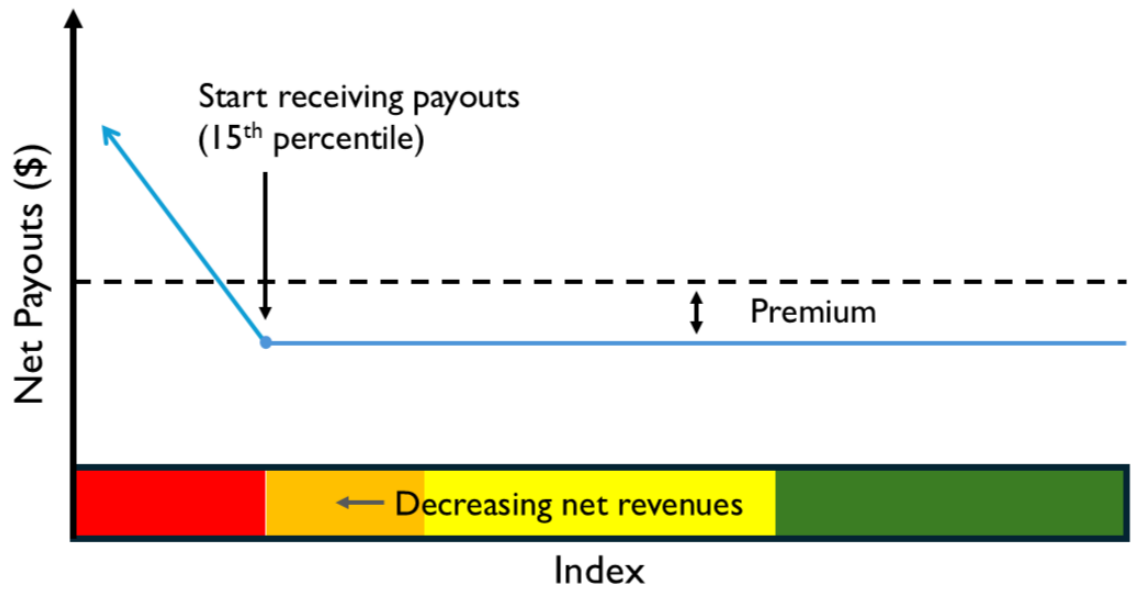

Figure 3: Generalized structure of an index-based insurance contract where the strike is set at the 15th percentile.

For a linear payout function, the magnitude of the payout (p) is determined by the severity of the loss defined by the difference between the strike (S) and the index (I):

$$p(\$B) = m \times max[S - I, 0] \tag{3}$$

where m is the slope of the payout function ($ payout per unit of the index). If the composite index is already in units of dollars, the payout function can be simplified to:

$$p(\$B) = max[S - I, 0] \tag{4}$$

Payouts during years when the composite index falls below the strike are in exchange for an annual premium paid from buyer to seller. The index insurance contracts in this study are priced using the Braun model [Braun, 2016], a multivariate linear econometric model based on reinsurance pricing data from 1997 to 2012, such that:

$$\begin{aligned} Pre = 221.04 \times EP + 175.08 \times PEAK - 103.58 \times SW + 161.85 \times ROLX \\ -159.76 \times IG + 26.57 \times BBSP \end{aligned}$$

where, Pre is the contract premium relative to the maximum possible payout (basis points). EP is the expected payout in relative to the maximum possible payout (percentage points). $PEAK$ is peak territory designation (1 = yes; 0 = no). SW indicates if the counterparty is well diversified (1 = yes; 0 = no). $ROLX$ is the synthetic rate on line index (reflects reinsurance market cycles) (points). IG indicates if the bond is investment grade (1 = yes; 0 = no). $BBSP$ is the corporate bond spread (percentage points).

This pricing method indicates that contracts with higher expected payouts and maximum possible payouts are more expensive. As many of the factors in the equation above can be considered consistent across the two scenarios (composite index and portfolio), a simplified Braun model used in Baum & Characklis (2020) is applied in this study:

$$Pre = 221.04 \times EP + 304.97 \tag{5}$$

Supplementary Materials Note B describes the assumptions made in developing equation 5. Baum and Characklis [2020] explored this simplified model for pricing hydrologic-based reinsurance and found that it performed well at recreating observed index-based contract premiums (Pearson correlation of 0.84) described in the Artemis database of catastrophe bond and reinsurance contracts [Artemis, 2018], which seems appropriate as the index insurance contracts considered here are structurally similar to reinsurance (i.e. risk transfer as opposed to risk pooling). The simplified Braun model as used in Baum and Characklis [2020] is used to price the composite index insurance contract and the portfolio of three independent index insurance contracts based on streamflow, CDD and natural gas prices.

2.4 Composite Index Insurance Contract Design

Index contracts designed to manage an individual risk, such as the financial risk arising from temperature or electricity price variability, are currently commercially available [Deng and Oren, 2006, CME group]. The Chicago Mercantile Exchange provides a platform for the exchange of index contracts based on a variety of weather conditions (commonly known as weather derivatives), such as temperature, rainfall, and snowfall. Contracts based on deviations from expected temperatures (e.g., measured as CDDs) are some of the most commonly used weather derivatives [Artemis, 2022]. Using index contracts to manage the drought risk of hydropower producers is less common, but there are still some instances of their current use. For example, Uruguay has purchased insurance to manage variability in precipitation as the country sources 80% of its electricity from hydropower [The World Bank, 2018]. Together in a portfolio, these existing types of contracts, based on individual indices, can be combined to manage PG&E's financial risk resulting from variable hydrology, temperature, and wholesale electricity prices. The objective of this work is to design a composite index that combines consideration of all three factors including annual streamflows as a measure of drought, annual CDD as a measure of demand, and average annual natural gas prices as a measure of market conditions and electricity prices. The ability of a composite index contract to predict net revenue fluctuations will then be evaluated relative to a portfolio of single index contracts designed to accomplish the same goal.

The composite index is constructed by regressing net revenue against the annual streamflow, CDD and natural gas prices over the 500 simulation years. The predicted value from the regression, given values of the three covariates is the composite index. 80% of the data were randomly selected for training whereas, the remaining 20% were used for testing as a means to prevent over-fitting.

$$\text{Net.Revenue}(\$B) \sim \alpha + \beta_1 \times sf + \beta_2 \times CDD + \beta_3 \times NG + \epsilon \tag{6}$$

$$I(\$B) = \alpha + \beta_1 \times sf + \beta_2 \times CDD + \beta_3 \times NG \tag{7}$$

where, sf is the annual streamflow, CDD is the summer temperature, a proxy for demand and NG is the natural gas price. The β's are the estimated coefficients and α is the intercept. ϵ are the residuals. The regression parameters are estimated using 80% of the data selected at random. $I(\$B)$ is the composite index and is computed using the estimated coefficients. Given the composite index and the selected strike level, the Braun method is used to price the composite index insurance contract.

2.5 Portfolio of Individual Contracts Design

To demonstrate the enhanced capability of the composite index-based contract, a portfolio of three separate single index contracts based on streamflows, CDD, and average annual wholesale electricity prices is also developed and their risk management performance is compared against that of the composite index-based contract described above. Risk management performance is measured as the cost of achieving the same risk management goal, which in this case is a specified level of variance reduction in net revenues. The Braun method is used for pricing all contracts. In order to develop the portfolio, the relationship between each individual index and net revenues is determined using linear regression (using the same statistical methods and training-testing split) as the composite index. This is used to identify the slope of the payout function ($ per unit of the index) (Equation

4) for each contract that will translate the difference between the strike and the observed index value into a dollar amount, which then becomes a payout that compensates for net revenue losses. For the portfolio of separate single indices, the strikes for each index are set such that they individually leads to minimization of the 95% VaR. Value at Risk (VaR) is used to estimate the maximum potential loss of an investment portfolio over a specified time period with a given confidence level, with a 95% VaR in this case indicating that there is a 5% chance that PG&E's net revenues will be lower than the VaR amount. The overall revenue for the portfolio of separate indices is computed by accounting for the three different payouts and premiums, as the revenue plus the payouts minus the premiums. The strike for the composite index is optimized such that the variance of the hedged revenues using the composite index is the same as the variance of the hedged revenues using the portfolio of separate single index contracts. The performance of the portfolio of single index contracts is then compared to that of the composite index contract.

2.6 Alternative Regulatory Scenario

Zeighami et al. [2023] explored the impacts of pollution taxes on West Coast grid operations and human health using CAPOW. The pollution taxes were incorporated into CAPOW by increasing the marginal cost of the power generators that release emissions of public health concern, namely SO_2, NO_x, and $PM_{2.5}$. Each generator's tax payment is measured in \$/MWh and is individually tailored to reflect the estimated human health damages resulting from its air emissions during power generation. The computed damages in Zeighami et al. are used as the thermal power-plant level pollution estimates in this study. The baseline no-tax scenario and alternative regulatory scenario use the same stochastic weather conditions across the 500 simulation year period but with different marginal costs of generators, which are then passed through CAPOW to simulate grid operations and through the PG&E financial model to estimate annual revenues. The effectiveness of the composite index insurance contract in reducing financial risk is compared against the portfolio of individual contracts for this alternative regulatory scenario with a pollution tax. The prevented pollution damages displayed in Figure S2 are the overall reduction in thermal generation across the no-tax (baseline scenario) versus the pollution tax scenario, and scaled by the plant level pollution damages as measured by $/MWh. The imposition of the pollution tax results in the highest prevented pollution damages occurring in years with low streamflows (drought) and hotter summers. Shifting generator dispatch to less polluting generators during hot and dry years has the significant potential to improve public health, but the enactment of pollution taxes also has the potential to introduce greater financial risk for PG&E.

3 Results

The first sub-section of the results includes assessment of the CAPOW and PG&E financial model by comparing simulation metrics against the publicly available metrics provided by PG&E. It is then followed by testing the efficacy of the composite index insurance contract using simulated hydrometeorological and market conditions produced by CAPOW in reducing risk in the unmanaged net revenues generated by the PG&E financial model. The composite index's performance and cost effectiveness are then compared to that of a portfolio of individual contracts based on the same indices that constitute the composite index. Both the composite index contract and the portfolio of individual contracts are assessed on the basis of their effectiveness in reducing the minimum net revenues, 95% VaR, and costs of risk mitigation. The composite index contract is then tested with altered system dynamics that is modeled as a response to air pollution taxes on power plants, a scenario that changes PG&E's financial risk. The latter scenario offers an additional opportunity to test the effectiveness of the composite index contract in limiting the exacerbated tail end financial risks associated with the imposition of the pollution tax and thus reduce one disincentive associated with an action intended to improve public health.

3.1 PG&E Financial Model Assessment

This section includes assessment and evaluation of the outputs from CAPOW and PG&E financial model against PG&E's publicly available financial metrics. The combined CAPOW and financial model generate outputs and simulations that agree well with observed values (Figure 4). Figure 4 (A) displays the distribution of the total deliveries in GWh across the generated simulations with the overall spread being from 80,000 - 85,000 GWh. The three red dots denote the deliveries by PG&E in the years 2016, 2017 and 2018. The extent of the annual energy deliveries in simulations covers the three years, but has a bias with respect to future potential years with lower energy deliveries.

Furthermore, the model accurately models the split in the revenue across the residential, commercial, industrial and agricultural sector. The mean across these sectors in the generated simulations are 41%, 39%,11% and 9% respectively. The mean of the recorded fraction sectoral revenue during 2016-2018 was 41%, 40%,12% and 8% respectively suggesting that the PG&E financial model captures the overall sectoral distribution within the utility.

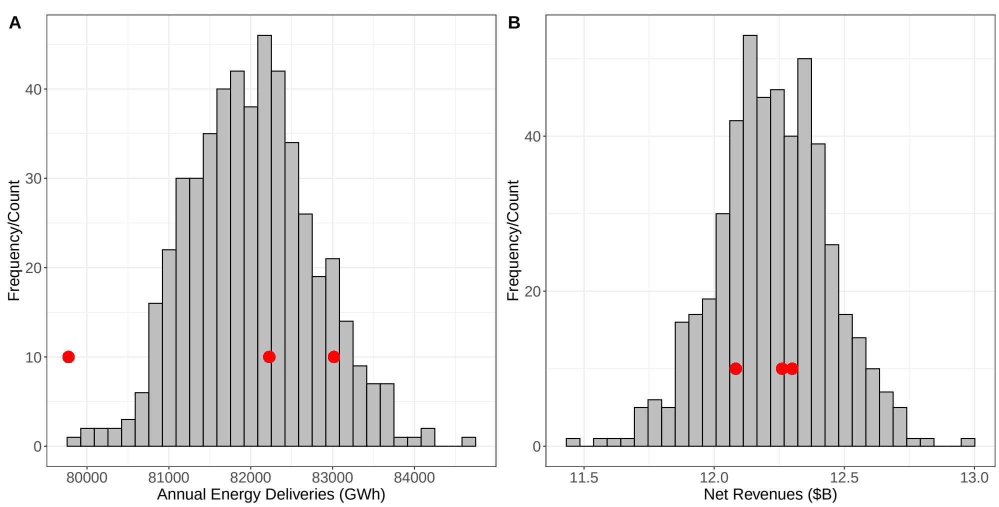

Figure 4: Comparison of CAPOW and Financial Model Results with observed values. (A) - Histogram of Annual Energy Deliveries (in GWh) by PG&E across the generated simulations. The three red dots correspond to the actual PG&E energy deliveries in 2016-2018. (B) - Histogram of PG&E's Annual Net Revenues (in $ billion) across the generated simulations. The three red dots correspond to the actual PG&E net revenues in 2016-2018.

The histogram in Figure 4 (B) displays the spread in net revenues generated by the financial model, with the red dots denoting the revenues in the years 2016, 2017 and 2018. The net revenue is an important parameter which determines the overall financial health of the utility, and the generated simulations appear to represent the spread in the distribution across the selected years reasonably well.

3.2 Influence of Market & Hydrometerological Conditions

The financial risk posed to PG&E by variability in annual streamflow, summer temperatures, and natural gas prices is depicted in Figure S3 and Figure 5. The net revenues across the simulations exhibit considerable variability ranging from 11.5-13 $ billion, and a mean of 12.2 $ billion. In this study, dry years are defined as annual streamflow below the 25th percentile, which reflects the U.S. Geological Survey's classification of "below normal" year [USGS, 2022]. Figure S3 (B) demonstrates that PG&E's mean net revenues typically suffer, albeit marginally, during years with low streamflows, which result in a decrease in hydropower generation and increased reliance on more expensive thermal generation. Simulation years with cool summers (defined as annual CDD below the 25th percentile) also result in lower mean net revenues (Figure S3 (C)). This is a consequence of a large fraction PG&E's revenue coming from selling power (for cooling and air-conditioning) to its residential customers that have higher rates in the summer due to seasonal pricing. Cooler summers reduce electricity demand, thereby reducing revenues. High natural gas prices (defined as prices above the 75th percentile across the simulations) lead to the largest reductions in net revenue (Figure S3 (D)). Natural Gas fired power plants are almost always the marginal generator within CAISO dictating the overall price per MWh, and at the annual time scale wholesale electricity prices are highly correlated with natural gas prices (Pearson correlation of 0.98 (Figure S4)). Consequently, higher prices of natural gas result in higher costs of energy procurement for PG&E, decreasing revenues since PG&E buys more power from CAISO than it sells into it.

Figure 5 displays the compound risk to net revenues due to the influence of natural gas prices, CDD and streamflow across the generated simulations. The dotted line denotes the 20th percentile of the simulated revenues. The strongest determinant of net revenue is the natural gas price, with higher natural gas prices associated with lower net revenues. The effect of CDD on net revenues is displayed using the color scheme and is less pronounced, but crucial. Net revenues are greater in years with higher CDD, which is attributed to the fact that total demand is highly correlated with CDD (Pearson correlation of 0.9).

The highlighted datapoints A, B and C in Figure 5, identify the years with the three highest CDD values respectively. Point A is the most profitable for the utility with the highest net revenues given that this year corresponds with low natural gas prices and high summer temperatures enabling the utility to buy power cheaply and sell larger quantities of it to its customers. The profitability changes a bit as we move to point B where the demand still exists due to high CDD, but the cost of generation goes up due to high natural gas prices, thereby reducing net revenue. Point C, D and E, refer to the years with the three highest market prices. Given the strong relationship between prices and net revenues points E and D represent the two lowest net revenues years. Point C represents a somewhat anomalous situation as it is a year with the third highest CDD, which would suggest high demand and net revenues, but natural gas prices are also high and this more than compensates and lowers net revenues. An additional confounding factor in the year represented by point C is that it corresponds to a low streamflow year thereby further reducing PG&E's generation and increasing costs, given that PG&E buys more power from CAISO than it sells into it. This situation highlights the double-edged sword of demand, as described by a year in which PG&E is forced to buy power at high costs to satisfy higher demand, thereby reducing its net revenues.

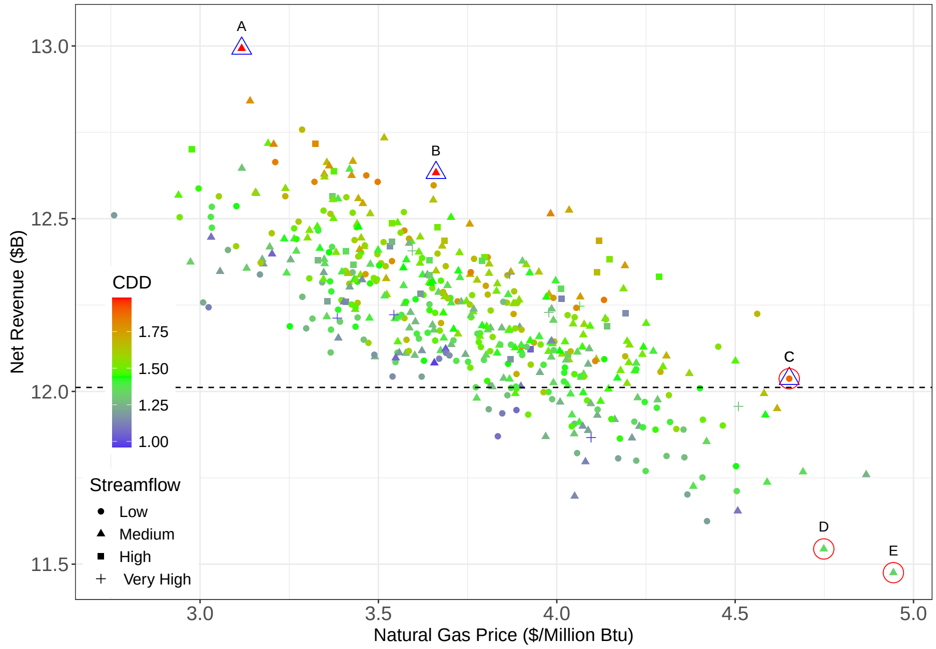

Figure 5: Compound Influence of Market & Hydrometerological Conditions. Net revenues versus natural gas prices across the simulations. Each point refers to an individual year. The color scheme depicts the CDD and the symbol shape denotes the streamflow across the simulations, with warmer colors denoting warmer summers (with higher electricity demand). The dotted line denotes the 20th percentile of the simulated revenues.

3.3 Composite Index

The multiple interactions between the market and hydrometerological conditions motivates the development of the composite index, which captures the joint correlation with net revenues. The composite index is constructed by regressing net revenue against the annual streamflow, CDD and natural gas prices, and is the predicted value of the regression, given values of the three covariates. Eighty percent of the data were randomly selected for training whereas, the remaining twenty percent were used for testing. The results from the regression on the training dataset are displayed in Table S1. The model testing error and training error were comparable indicating no presence of overfitting (Figure S5). Overall, the composite index (I) is computed as follows:-

$$I(\$B) = 0.074 \times sf + 0.108 \times CDD - 0.161 \times NG + 12.227 \tag{8}$$

where, sf is the annual streamflow, CDD is the cooling degree days (a measure of summer temperature) and NG is the annual mean natural gas price. All three covariates were standardized, transforming them to a mean of zero and standard deviation of one. The predicted index values were calculated using the deterministic component of the regression equation, omitting the stochastic error term to ensure contractual transparency and computational certainty in the insurance settlement process.

Figure 6 displays the correlation matrix across the variables used to construct the portfolio of instruments (streamflow, CDD and Natural Gas), as well as how each correlates with net revenues and the composite index. The Pearson correlation value for each variable pair is denoted within the sub-plot along with the linear fit estimated from the entire set of simulations. Streamflow and CDD are negatively correlated with a coefficient of -0.26 (p=2.1e-09), a relation between dry years and hot summers. Natural gas price does not vary (near zero correlation) with streamflow and CDD largely because natural gas prices are largely set by national and global markets, such that variability in demands in California alone do not have much of an impact.

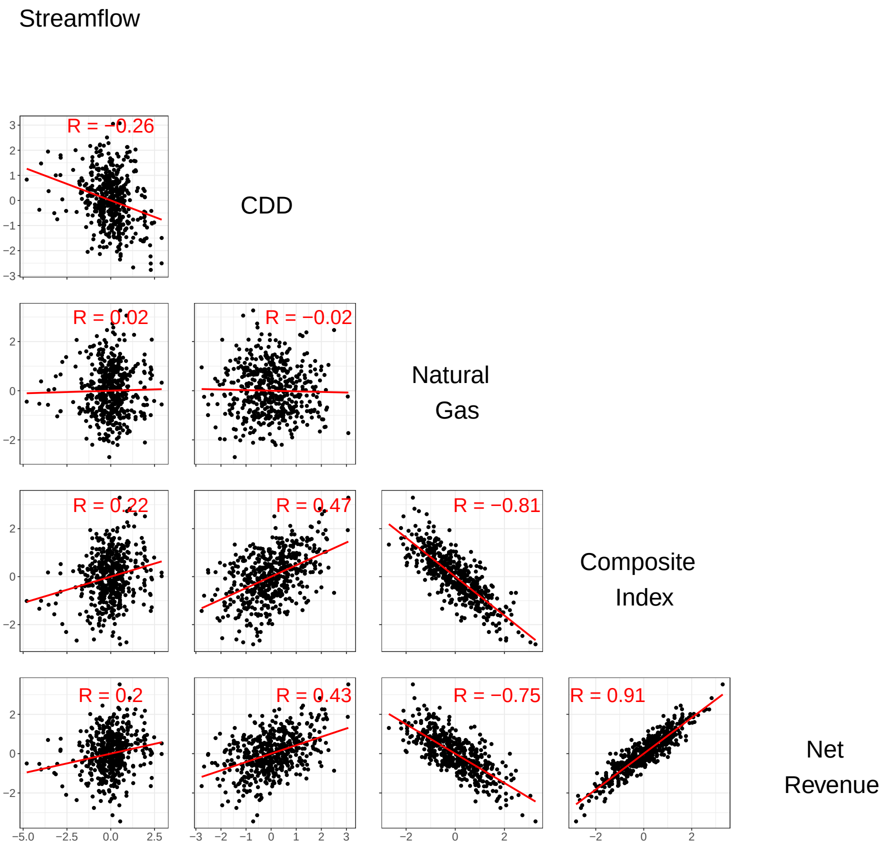

Figure 6: Correlation matrix of annual streamflow, CDD, natural gas prices, the composite index, and net revenues. All values are standardized. The Pearson correlation coefficients for each variable pair are denoted in red within the sub-plot.

Streamflow and net revenue are weakly positively correlated (R=0.20, p =7.4e-06), indicating that low streamflow years contribute to lowering net revenues. Net revenues and CDD, have a stronger positive correlation (R=0.43, $p < 2.2e\text{-}16$), indicating that net revenues improve with increasing summer temperatures. Net revenues are negatively correlated with natural gas prices (R=-0.75, $p < 2.2e\text{-}16$), displaying the effect of high natural gas prices in reducing the overall net revenues. Each of these three variables are used as individual risk transfer instruments within the portfolio of available instruments, and are compared against the composite index based instrument.

While these individual relationships capture one-to-one correlations between each variable and net revenue, the composite index (eqn. 8) is much more highly correlated with net revenues (Pearson correlation of 0.91, $p < 2.2e\text{-}16$) than any of the individual components. The composite index captures these relationships in a way that indices based on each individual component do not, accounting for interactions between components (e.g. the joint probability of drought and heatwave) that amplify or reduce net revenue losses relative to what is observed when only considering the effects of each component individually. In this way, a contract based on the composite index decreases basis risk relative to what is observed when considering the effects of each component individually, reducing the incidence of over/under-payment and leading to a more effective financial instrument. While this finding was foreshadowed in previous research, it has not been tested or quantified.

3.4 Composite Index Contract Performance

A 100-year time series (subset of simulated years) illustrates the performance of the composite index contract (Figure S6) and demonstrates that it is effective in raising the net revenue floor (i.e., the lowest net revenues) experienced by the utility over the period in question. A similar plot displaying the effectiveness of the composite index contract across all the simulation years is attached in the supplement (Figure S7). The mean net revenues over this period decreases due to the annual contract premium, but payouts are reliably triggered during the worst performing years, limiting the utility's losses during adverse conditions.

The composite index contract improves the revenue floor (worst-case net revenues) from \$11.47 billion to \$11.76 billion (an improvement of almost \$300 million) and raises the 5th percentile risk threshold from \$11.87 billion to \$11.91 billion (an improvement of \$45 million) in exchange for an annual premium of \$47.5 million that lowers PG&E's mean net revenue accordingly. The portfolio of single index contracts is also designed to limit low net revenue years and reproduce the same overall variability in net revenues (measured in terms of variance) as the composite index contract. However, it does not perform as well as the composite index contract in limiting the net revenue floor experienced, and it costs significantly more (Table 1), largely as a result of basis risk. The composite index contract reduces the variance of PG&E's net revenues to a level of 37,100 ($\$M^2$) at a premium cost of \$45.7 million annually, which is significantly less expensive than the cost of a portfolio of individual contracts (\$82.5 million) that produces the same net revenue variability. The greater aggregate premium cost of the portfolio results from its higher basis risk, which leads to overpayments during years without substantial losses and a higher expected aggregate payout. The higher aggregate payout is a function of the lower correlation between utility losses and payouts, thus more payouts are required to achieve the same risk reduction as that reached via the composite index contract. The selected strike for the composite index is near the 15th percentile, refer Table S2 for the influence of the strike on risk management.

Table 1: Performance of the composite index contract and the portfolio of individual contracts compared to unmanaged net revenues.

	Unmanaged Net Revenues	Net Revenues Managed with Composite Index	Net Revenues Managed with Portfolio
Premium ($M)	–	45.5	81.3
Expected Payout ($M)	–	15.7	27.3
Loading ($M)	–	29.8	54
Mean Net Revenue ($M)	12,226	12,196	12,172
Net Revenue Variance ($M)^2	47,280	37,090	37,100
Net Revenue 5th Percentile ($M)	11,871	11,915	11,870
Minimum Net Revenue ($M)	11,475	11,764	11,656

Further evidence of basis risk is seen in histograms comparing PG&E's unmanaged losses with the payouts from both the composite index contract and the portfolio (Figure 7). In this case, the "portfolio payout" is the aggregate payout calculated by summing the payouts from the individual contracts in the portfolio. The areas of the payout distribution that do not overlap with the distribution of unmanaged losses represent over/under-payments. Comparatively, the composite index contract does not produce many instances of overpayments. There is still some level of basis risk with the composite index contract, and this sometimes leads to small underpayments during years when PG&E has accrued unmanaged losses, but these are relatively minor and occur less frequently than the portfolio strategy's overpayments.

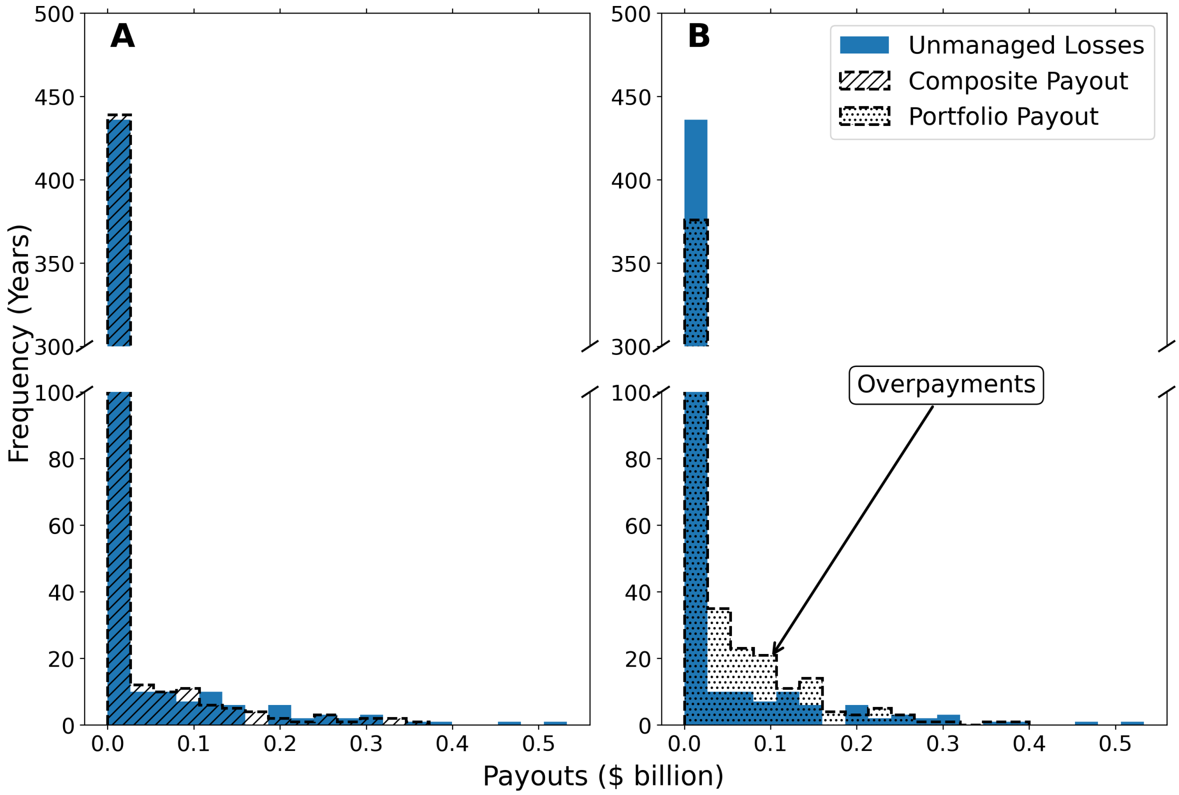

Figure 7: PG&E's simulated unmanaged losses and payouts from (A) composite index insurance and (B) a portfolio of contracts based on the same indices as the composite index. The "portfolio payout" is the aggregate payout calculated by summing the payouts from the individual contracts in the portfolio.

A short illustrative time series of payouts (sub-set across of simulated years) from both the composite index contract and the three individual contracts in the portfolio shows the individual index contracts are frequently triggered during years without unmanaged losses (i.e., unmanaged net revenues below the 15th percentile) (Figure 8). Meanwhile, the composite index contract is reliably triggered during the worst net revenue years, and the magnitude of payouts from the composite contract better correlates with the unmanaged losses than those from the individual contracts.

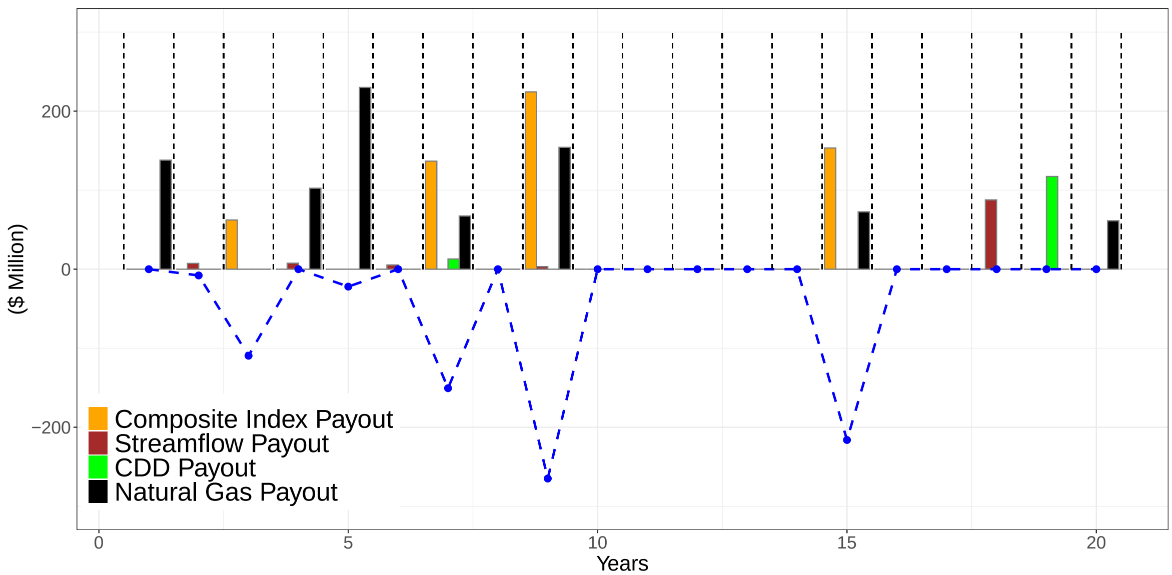

Figure 8: Time series subset of the payouts from the composite index insurance and the payouts from the portfolio of contracts against the unmanaged losses (blue dotted line) experienced by PG&E during those years.

3.5 Application to an Alternative Future Scenario

The simulations from CAPOW and the PG&E financial model allow for the financial implications of pollution taxes for PG&E to be explored and the effectiveness of the composite index contract to be tested under this alternative regulatory scenario.

Overall Changes in Net Revenue

Annual net revenues across the tax and no tax scenarios are shown in Figure S8. The pollution tax reduces PG&E's annual mean net revenues, but also increases the financial risk of very low net revenues (i.e. greater tail risk). While the mean net revenues decrease by $ 327 million, the minimum net revenue reduces by $

369 million due to the pollution tax, whereas the 95% VaR value decreases by 360 million USD.

Constructing the new Composite Index

Pollution taxes alter how PG&E is financially impacted by hydrometeorological extremes. In the baseline generation scenario with no pollution taxes, the utility financially benefits from summers with high temperatures as this increases demand for electricity and PG&E's revenues from electricity sales (Figures 6). However, with the pollution tax implemented, the correlation between higher temperatures and the resulting net revenues is reduced (Pearson correlation of 0.3 (p=1.4e-11) instead of the earlier 0.43) as PG&E brings more polluting power plants online during periods of high demand and the pollution tax increases PG&E's costs (Figure S9). On the other hand, the relationship between streamflow and net revenues becomes stronger, with lower streamflow years associated with lower revenues in this regulatory scenario (Pearson correlation of 0.28 (p=9.1e-11) instead of the earlier 0.19) (Figure S9). Furthermore, average annual wholesale electricity prices are higher with pollution taxes, and these prices now have stronger correlations with streamflow and CDD when compared to the no-tax scenario. This increased correlation relative to the baseline scenario is in part due to the pollution taxes, which drive up wholesale electricity prices during periods of high demand and loss of hydropower forces the utility to run more polluting plants and incur higher tax payments.

The composite index insurance contract accounts for these shifted relationships and enables the utility to reduce its losses. By limiting the losses PG&E would experience as a result of the pollution tax, the organization should be able to more easily manage the implementation of the tax thereby reducing at least some of potential arguments it. The composite index is constructed using the same methodology as in the no tax scenario. Refer to Supplement Note D for further details. The composite index (I) is slightly modified in this altered scenario to reflect the effects of the shifted relationships with demand:

$$I(\$B) = 0.094 \times sf + 0.091 \times CDD - 0.18 \times NG + 11.9 \tag{9}$$

where, sf is the annual streamflow, CDD is the cooling degree days (a measure of summer temperatures), and NG is the annual mean natural gas price. All three covariates were standardized, transforming them to a mean of zero and standard deviation of one. The adjusted composite index again correlates very well with PG&E's net revenues (R^2 of 0.91 (Figure S9)), and a contract based on this modified index is designed using a strike at the 18th percentile that, similar to the baseline contract, corresponds to payouts being triggered roughly one in six years.

Effectiveness of Composite Index

The composite index contract improves the worst-case net revenues in a pollution tax scenario from \$11.1 billion to \$11.4 billion (an improvement of over \$300 million) and raises the 5th percentile risk threshold from \$11.51 billion to \$11.57 billion (an improvement of \$64 million) in exchange for an annual premium of \$63 million that lowers PG&E's mean net revenue accordingly. Under this altered regulatory scenario, PG&E's net revenues are lower during years when the prevented pollution damages are lower, given that high natural gas prices lower net revenues and incentivize the use of dirtier alternative source thermal plants. Nonetheless even in these years, where the pollution tax reduces PG&E's revenues, the composite index contract helps increase the revenue floor. The use of this composite index contract therefore seems capable of significantly reducing the increased financial risk that would accompany the implementation of a pollution tax, especially during years with extremely unfavourable hydrometeorology. The composite index contract also significantly reduces overall net revenue variability, decreasing the coefficient of variation in net revenues from 0.02 to 0.017 (56500 ($\$M^2$) to 42040 ($\$M^2$)). For comparison, the composite index contract implemented under the first scenario without pollution taxes results in a smaller reduction in the coefficient of variation from 0.018 to 0.016 (47300 ($\$M^2$) to 37100 ($\$M^2$)). Thus, the composite index contract is even more effective at reducing financial risk in a scenario involving pollution taxes than it is in a scenario with no pollution taxes.

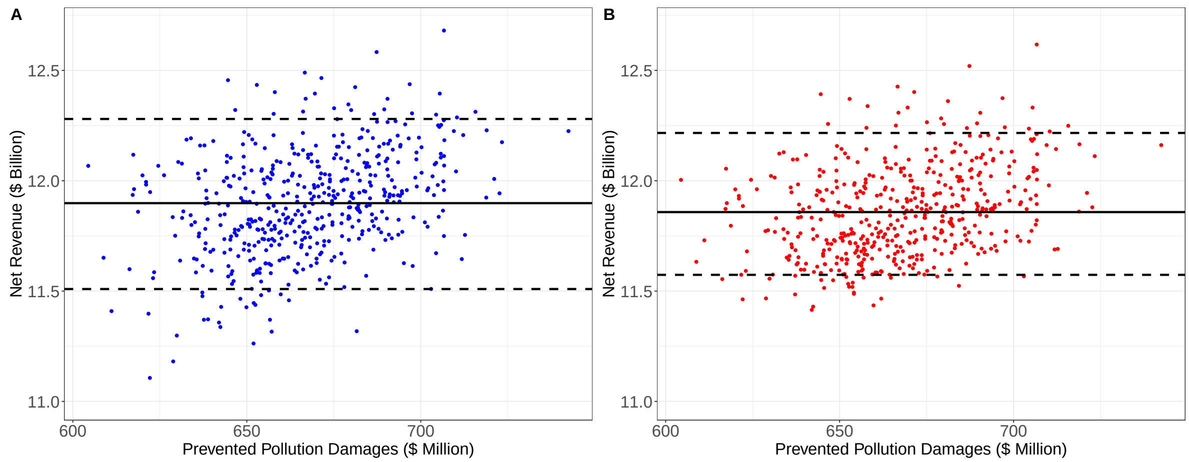

Figure 9: Effectiveness of the composite index during the pollution tax scenario. (A) Unmanaged net revenues and (B) net revenues managed using a composite index contract versus the prevented pollution damages within the California. For both sub-plots the solid black line denotes the mean, whereas the dotted black lines denote the 5th and 95th percentile of the net revenues.

4 Discussion

These results suggest that financial contracts based on a composite index can more cost-effectively manage the financial risk imposed on electric utilities as a result of extreme hydrometeorological conditions and the higher electricity market prices that accompany them. A financial risk management strategy based on a composite index contract outperformed a portfolio of single index contracts with the same constituent indices by achieving the same variance in net revenues for roughly half the price, largely due to the lower basis risk associated with the composite index contract. This is driven by the higher correlation between PG&E's net revenues and the composite index, a result of the composite index incorporating the compound effect of all three index components, which can amplify or diminish net revenue losses due to correlations between factors such as droughts and heatwaves. Vertically integrated utilities with diversified generation mixes, especially those that include a large fraction of renewables whose generation is highly influenced by hydrometeorological conditions, could benefit most from composite index contracts, as environmental factors have a larger influence on their overall generation mix, a situation likely to impact more utilities in the future. A primary benefit of the improved risk management strategies that result could be a better credit rating and lower interest rates, reducing overall utility borrowing rates, which should eventually lead to lower consumer prices. With respect to steps needed to develop a commercially viable product, the composite index would need to be modified to account for model error, as CAPOW tends to overestimate the impacts of some hydrometeorological conditions due to assumptions made in the model (e.g., simplified transmission infrastructure topology). In addition, this work uses stationary hydrometeorological conditions, meaning contract premiums may need to be revised to account for climate change impacts on the frequency and magnitude of extreme hydrometeorological events.

The coincidence of extremely hot and dry periods, posing a threat to both the financial stability of the utility and the public health of nearby communities through the increased use of more heavily polluting thermal generation is also an area that should draw continued interest. While a pollution tax on the resulting higher emissions can reduce pollution damages, it is also likely to increase a utility's financial risk. Under a scenario with a pollution tax, hot and dry periods generally decrease net revenues as the utility is forced to dispatch its most polluting and thus most highly taxed, power plants in order to meet demand. The composite index contract shows promise in terms of effectively reducing the increased financial risk driven by a pollution tax. Applying the composite index contract to a scenario that includes a pollution tax suggests that the contract can be used to facilitate improved public health by removing disincentives for actions like a pollution tax that may lead to greater financial risk.

Further research might include explore different types of contract structures and risk management strategies for managing net revenue variability at shorter timescales (e.g., during blackouts). A composite index contract developed for use during conditions at shorter timescales could offer similar advantages, though the types of risks being addressed might change (e.g., at shorter timescales, heat waves pose more of a financial risk than at an annual timescale). Contracts with shorter durations would be especially useful in a pollution tax scenario, as pollution taxes can fail to reduce pollution damages during extremely hot days in late summer when hydropower is simultaneously low, and all available generation sources must be dispatched to avoid blackouts as described by Zeighami et al. [2023].

5 Conclusion

Variability in hydrometeorological conditions poses a significant financial risk to electric utilities, a risk that arises from intermittent fluctuations in electricity supply and demand that drive unpredictable swings in costs and revenues. A composite index insurance contract tailored to manage these hydrometeorological risks is just as effective as, and significantly less expensive than a portfolio of separate contracts currently commercially available. Taking effective steps to stabilize net revenues with financial instruments can help satisfy investors, lenders, and others (e.g., credit rating agencies) that a utility's financial risk is being better managed, contributing to both improved long-term financial stability and lower costs. These findings may have broad applicability as investor-owned electric utilities accounted for 34.7% of total electricity generation in the United States as of 2022 [Edison Electric Institute, 2023]. Concerns over climate change have resulted in electric utilities coming under increasing scrutiny regarding their financial exposure to hydrometeorological risks, making new tools and strategies for managing these risks increasingly important.

Data and Code Availability

The code needed to replicate the analysis can be found at `https://github.com/yashamonkar/CompositeIndexInsurance`. The underlying methodology used to generate the simulations follows Zeighami et al. [2023]. The entire data along with the underlying simulations and the code used in this study is made publicly available at https://zenodo.org/records/14933915.

References

Amir AghaKouchak, Linyin Cheng, Omid Mazdiyasni, and Alireza Farahmand. Global warming and changes in risk of concurrent climate extremes: Insights from the 2014 California drought. *Geophysical Research Letters*, 41(24):8847–8852, 2014. ISSN 1944-8007. doi: 10.1002/2014GL062308. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/2014GL062308. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/2014GL062308.

Allianz SE. The weather business report. Technical report, 2013. URL https://commercial.allianz.com/news-and-insights/reports/the-weather-business-report.html.

Artemis. Catastrophe Bond & Insurance-Linked Securities Deal Directory - Artemis.bm, 2018. URL https://www.artemis.bm/deal-directory/.

Artemis. What are weather derivatives? - Artemis - Resource Library, 2022. URL https://www.artemis.bm/library/what-are-weather-derivatives/.

Aspen Environmental Group and M. Cubed. Potential changes in hydropower production from global climate change in California and the western United States. Technical report, 2005. URL https:

//relicensing.pcwa.net/var/www/html/publichtml/documents/Library/PCWA-L-208.pdf.

Bryson Bates, Zbigniew Kundzewicz, and Shaohong Wu. *Climate Change and Water*. Intergovernmental Panel on Climate Change Secretariat, June 2008. ISBN 978-92-9169-123-4. URL https://www.taccire.sua.ac.tz/handle/123456789/552. Accepted: 2017-10-16T06:50:49Z.

Rachel Baum and Gregory W. Characklis. Mitigating Drought-Related Financial Risks for Water Utilities via Integration of Risk Pooling and Reinsurance. *Journal of Water Resources Planning and Management*, 146 (6):05020007, June 2020. ISSN 1943-5452. doi: 10.1061/(ASCE)WR.1943-5452.0001202. URL https://ascelibrary.org/doi/10.1061/%28ASCE%29WR.1943-5452.0001202. Publisher: American Society of Civil Engineers.

Alex Blomfield and J Plummer. The Allocation and Documentation of Hydrological Risk. *International Journal on Hydropower and Dams*, 2014, October 2014.

Alexander Braun. Pricing in the Primary Market for Cat Bonds: New Empirical Evidence. *Journal of Risk and Insurance*, 83(4):811–847, 2016. ISSN 1539-6975. doi: 10.1111/jori.12067. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jori.12067. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jori.12067.

Markus Burger, Bernhard Graeber, and Gero Schindlmayr. *Managing Energy Risk:*

An Integrated View on Power and Other Energy Markets. John Wiley & Sons, September 2014. ISBN 978-1-118-61863-9. Google-Books-ID: wJjPAwAAQBAJ.

C2ES. Carbon Tax Basics, 2022. URL `https://www.c2es.org/content/carbon-tax-basics/`.

California Energy Commission. Electric Load Serving Entities (IOU & POU), 2021. URL `https://cecgis-caenergy.opendata.arcgis.com/datasets/CAEnergy::electric-load-serving-entities-iou-pou/about`.

California Natural Resources Agency. NHD Major Lakes and Reservoirs Shapefile, 2020. URL `https://data.cnra.ca.gov/dataset/national-hydrography-dataset-nhd/resource/ec84510b-2cd3-41c1-9f3e-849209582a72`.

California Natural Resources Agency. NHD Major Rivers Shapefile, 2022. URL `https://data.cnra.ca.gov/dataset/national-hydrography-dataset-nhd/resource/510abd22-f63b-4981-a17e-3c76cec5fa18`.

Kristina Yuzva Clement, W. J. Wouter Botzen, Roy Brouwer, and Jeroen C. J. H. Aerts. A global review of the impact of basis risk on the functioning of and demand for index insurance. *International Journal of Disaster Risk Reduction*, 28:845–853, June 2018. ISSN 2212-4209. doi: 10.1016/j.ijdrr.

2018.01.001. URL https://www.sciencedirect.com/science/article/pii/S2212420918300049.

CME group. Weather Products Homepage - CME Group. URL http://www.cmegroup.com/trading/weather/.

Owen Comstock. In 2017, U.S. electricity sales fell by the greatest amount since the recession - U.S. Energy Information Administration (EIA), 2018. URL https://www.eia.gov/todayinenergy/detail.php?id=35612.

Simona Denaro, Andrea Castelletti, Matteo Giuliani, and Gregory W. Characklis. Fostering cooperation in power asymmetrical water systems by the use of direct release rules and index-based insurance schemes. *Advances in Water Resources*, 115:301–314, May 2018. ISSN 0309-1708. doi: 10.1016/j.advwatres.2017.09.021. URL https://www.sciencedirect.com/science/article/pii/S0309170817305304.

S. J. Deng and S. S. Oren. Electricity derivatives and risk management. *Energy*, 31(6):940–953, May 2006. ISSN 0360-5442. doi: 10.1016/j.energy.2005.02.015. URL https://www.sciencedirect.com/science/article/pii/S0360544205000496.

Jonathan DeVilbiss and Mark Morey. June heat wave in the Northwest United States resulted in more demand for electricity - U.S. Energy Information Administration (EIA), 2021. URL https://www.eia.gov/todayinenergy/detail.php?id=48796.

Scott DiSavino. California drought cuts hydropower, boosts natgas prices | Reuters, 2021. URL https://www.reuters.com/business/energy/california-drought-cuts-hydropower-boosts-natgas-prices-2

Edison Electric Institute. Industry Data Overview, 2023. URL https://www.eei.org/resources-and-media/industry-data.

Benjamin T. Foster, Jordan D. Kern, and Gregory W. Characklis. Mitigating hydrologic financial risk in hydropower generation using index-based financial instruments. *Water Resources and Economics*, 10:45–67, April 2015. ISSN 2212-4284. doi: 10.1016/j.wre.2015.04.001. URL https://www.sciencedirect.com/science/article/pii/S2212428415000146.

Peter Gleick. Impacts of California's Five-Year (2012-2016) Drought on Hydroelectricity Generation. Technical report, Pacific Institute, 2017.

Andrew L. Hamilton, Gregory W. Characklis, and Patrick M. Reed. Managing Financial Risk Trade-Offs for Hydropower Generation Using Snowpack-Based Index Contracts. *Water Resources Research*, 56(10):e2020WR027212, 2020. ISSN 1944-7973. doi: 10.1029/2020WR027212. URL https://onlinelibrary.

wiley.com/doi/abs/10.1029/2020WR027212. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2020WR027212.

Julio E. Herrera-Estrada, Noah S. Diffenbaugh, Fabian Wagner, Amy Craft, and Justin Sheffield. Response of electricity sector air pollution emissions to drought conditions in the western United States. *Environmental Research Letters*, 13(12):124032, December 2018. ISSN 1748-9326. doi: 10.1088/1748-9326/aaf07b. URL https://dx.doi.org/10.1088/1748-9326/aaf07b. Publisher: IOP Publishing.

Tyler Hodge. Wholesale electricity prices trended higher in 2021 due to increasing natural gas prices - U.S. Energy Information Administration (EIA), 2022. URL https://www.eia.gov/todayinenergy/detail.php?id=50798.

John C. Hull. *Options, futures, and other derivatives*. Pearson, 2022. ISBN 978-1-292-41062-3. URL https://thuvienso.hoasen.edu.vn/handle/123456789/12872.

Laurie S. Huning and Steven A. Margulis. Climatology of seasonal snowfall accumulation across the Sierra Nevada (USA): Accumulation rates, distributions, and variability. *Water Resources Research*, 53(7):6033–6049, 2017. ISSN 1944-7973. doi: 10.1002/2017WR020915. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/2017WR020915. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/2017WR020915.

Sarah B. Kapnick, Xiaosong Yang, Gabriel A. Vecchi, Thomas L. Delworth, Rich Gudgel, Sergey Malyshev, P. C. D. Milly, Elena Shevliakova, Seth Underwood, and Steven A. Margulis. Potential for western US seasonal snowpack prediction. *Proceedings of the National Academy of Sciences*, 115(6):1180–1185, February 2018. doi: 10.1073/pnas.1716760115. URL https://www.pnas.org/doi/abs/10.1073/pnas.1716760115. Publisher: Proceedings of the National Academy of Sciences.

Jordan D. Kern, Gregory W. Characklis, and Benjamin T. Foster. Natural gas price uncertainty and the cost-effectiveness of hedging against low hydropower revenues caused by drought. *Water Resources Research*, 51(4):2412–2427, 2015. ISSN 1944-7973. doi: 10.1002/2014WR016533. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/2014WR016533. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/2014WR016533.

Jordan D. Kern, Yufei Su, and Joy Hill. A retrospective study of the 2012–2016 California drought and its impacts on the power sector. *Environmental Research Letters*, 15(9):094008, August 2020. ISSN 1748-9326. doi: 10.1088/1748-9326/ab9db1. URL https://dx.doi.org/10.1088/1748-9326/ab9db1. Publisher: IOP Publishing.

Qinqin Kong, Selma B. Guerreiro, Stephen Blenkinsop, Xiao-Feng Li, and Hayley J. Fowler. Increases in summertime concurrent drought and heatwave in Eastern China. *Weather and Climate Extremes*, 28: 100242, June 2020. ISSN 2212-0947. doi: 10.1016/j.wace.2019.100242. URL https://www.sciencedirect.com/science/article/pii/S2212094719300702.

Wendy Larson, Paul Freedman, Viktor Passinsky, Edward Grubb, and Peter Adriaens. Mitigating Corporate Water Risk: Financial Market Tools and Supply Management Strategies, September 2012. URL https://papers.ssrn.com/abstract=2159370.

Ziyue Li, Zhao Zhang, Jing Zhang, Yuchuan Luo, and Liangliang Zhang. A new framework to quantify maize production risk from chilling injury in Northeast China. *Climate Risk Management*, 32:100299, January 2021. ISSN 2212-0963. doi: 10.1016/j.crm.2021.100299. URL https://www.sciencedirect.com/science/article/pii/S2212096321000280.

N. Madden, A. Lewis, and M. Davis. Thermal effluent from the power sector: an analysis of once-through cooling system impacts on surface water temperature. *Environmental Research Letters*, 8(3):035006, July 2013. ISSN 1748-9326. doi: 10.1088/1748-9326/8/3/035006. URL https://dx.doi.org/10.1088/1748-9326/8/3/035006. Publisher: IOP Publishing.

J. Scott Mathews. Dog Days and Degree Days. Technical report, CME Group, 2009. URL https://www.cmegroup.com/trading/weather/files/WT133WeatherWhitePaperFinal.pdf.

Ben McMahan and Andrea K. Gerlak. Climate risk assessment and cascading impacts: Risks and opportunities for an electrical utility in the U.S. Southwest. *Climate Risk Management*, 29:100240, January 2020. ISSN 2212-0963. doi: 10.1016/j.crm.2020.100240. URL https://www.sciencedirect.com/science/article/pii/S2212096320300309.

Conor Meenan, John Ward, and Robert Muir-Wood. Disaster risk finance: A toolkit | PreventionWeb, May 2019. URL https://www.preventionweb.net/publication/disaster-risk-finance-toolkit.

Moody's. Rating Methodology:US Public Power Electric Utilities with Generation Ownership Exposure. Technical report, Moody's Investors Service, 2013. URL https://ratings.moodys.com/api/rmc-documents/398041.

Sourav Mukherjee, Moetasim Ashfaq, and Ashok Kumar Mishra. Compound Drought and Heatwaves at a Global Scale: The Role of Natural Climate Variability-Associated Synoptic Patterns and Land-Surface Energy Budget Anomalies. *Journal of Geophysical Research: Atmospheres*, 125(11):e2019JD031943, 2020. ISSN 2169-8996. doi: 10.1029/2019JD031943. URL https://onlinelibrary.wiley.com/doi/abs/10.1029/2019JD031943. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2019JD031943.

C. S. Murthy, Malay Kumar Poddar, Karun Kumar Choudhary, Varun Pandey, P. Srikanth, Siddesh Ramasubramanian, and G. Senthil Kumar. Paddy crop insurance using satellite-based composite index of crop performance. *Geomatics, Natural Hazards and Risk*, 13(1):310–336, December 2022. ISSN 1947-5705. doi: 10.1080/19475705.2021.2025155. URL https://doi.org/10.1080/19475705.2021.2025155. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/19475705.2021.2025155.

National Drought Mitigation Center. Data Tables | U.S. Drought Monitor, 2023. URL https://droughtmonitor.unl.edu/dmData/DataTables.aspx.

Daisy Nguyen. PG&E warns of more rolling outages amid California heat wave. *Washington Post*, August 2020. ISSN 0190-8286. URL https://www.washingtonpost.com/business/california-heat-spurs-1st-rolling-power-outages-since-201 2020/08/14/0f7f0f82-deab-11ea-b4f1-25b762cdbbf4 story.html.

PG&E Corporation. 2018 Form 10-K. Technical report, 2018. URL https://s1.q4cdn.com/880135780/files/docfinancials/2018/q4/2018-Form-10-K.pdf.

PG&E Corporation. 2019 Form 10-K. Technical report, 2019. URL https:

//s1.q4cdn.com/880135780/files/docfinancials/2019/q4/5cc337b8-8359-4e4a-9465-fe813fc00244.pdf.

PG&E Corporation. 2020 Form 10-K. Technical report, 2020a. URL https://s1.q4cdn.com/880135780/files/docfinancials/2020/q4/PGE-12.31.20-10K-(FINAL)(1).pdf.

PG&E Corporation. Corporate Responsibility and Sustainability. Technical report, 2020b. URL https://www.pgecorp.com/content/dam/pgecorp/language-masters/en/sustainability/corporate-responsibility-sustainability/reports/2020/assets/PGECRSR2020.pdf.

PG&E Corporation. Hydroelectric System, 2022. URL https://www.pge.com/en/about/pge-systems/hydroelectric-system.html.

Francisco Pérez-González and Hayong Yun. Risk Management and Firm Value: Evidence from Weather Derivatives. *The Journal of Finance*, 68(5): 2143–2176, 2013. ISSN 1540-6261. doi: 10.1111/jofi.12061. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12061. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12061.

Neil Schofield. Commodity Derivatives: Markets and Applications, 2nd Edition | Wiley, 2021. URL https://www.wiley.com/en-us/Commodity+

Derivatives%3A+Markets+and+Applications%2C+2nd+Edition-p-9781119349259.

Mark C. Serreze, Martyn P. Clark, Richard L. Armstrong, David A. McGinnis, and Roger S. Pulwarty. Characteristics of the western United States snowpack from snowpack telemetry (SNO) data. *Water Resources Research*, 35(7):2145–2160, 1999. ISSN 1944-7973. doi: 10.1029/1999WR900090. URL https://onlinelibrary.wiley.com/doi/abs/10.1029/1999WR900090. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/1999WR900090.

Tom Serzan. With Late Summer Degree Day Swings, Q3 Utility Sales, Earnings A Wild Card, 2019. URL https://www.spglobal.com/marketintelligence/en/news-insights/research/with-late-summer-degree-day-swings-q3-utility-sales-earni

Hong Shi and Zhihui Jiang. The efficiency of composite weather index insurance in hedging rice yield risk: evidence from China. *Agricultural Economics*, 47 (3):319–328, 2016. ISSN 1574-0862. doi: 10.1111/agec.12232. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/agec.12232. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/agec.12232.

S. Shukla and D. P. Lettenmaier. Seasonal hydrologic prediction in the United States: understanding the role of initial hydrologic conditions and seasonal climate forecast skill. *Hydrology and Earth System Sci-*

ences, 15(11):3529–3538, November 2011. ISSN 1027-5606. doi: 10.5194/hess-15-3529-2011. URL https://hess.copernicus.org/articles/15/3529/2011/. Publisher: Copernicus GmbH.

Yufei Su, Jordan D. Kern, Simona Denaro, Joy Hill, Patrick Reed, Yina Sun, Jon Cohen, and Gregory W. Characklis. An open source model for quantifying risks in bulk electric power systems from spatially and temporally correlated hydrometeorological processes. *Environmental Modelling & Software*, 126:104667, April 2020a. ISSN 1364-8152. doi: 10.1016/j.envsoft.2020.104667. URL https://www.sciencedirect.com/science/article/pii/S1364815219309739.

Yufei Su, Jordan D. Kern, Patrick M. Reed, and Gregory W. Characklis. Compound hydrometeorological extremes across multiple timescales drive volatility in California electricity market prices and emissions. *Applied Energy*, 276:115541, October 2020b. ISSN 0306-2619. doi: 10.1016/j.apenergy.2020.115541. URL https://www.sciencedirect.com/science/article/pii/S0306261920310539.

The World Bank. Uruguay buys insurance against lack of rain and high oil prices, 2018. URL https://www.worldbank.org/en/results/2018/01/10/uruguay-insurance-against-rain-oil-prices.

Calum G. Turvey. Weather Derivatives for Specific Event Risks in Agriculture. *Applied Economic Perspectives and Policy*, 23(2):333–351, 2001. ISSN 2040-

5804. doi: 10.1111/1467-9353.00065. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/1467-9353.00065. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1467-9353.00065.

US EIA. Electric generator dispatch depends on system demand and the relative cost of operation - U.S. Energy Information Administration (EIA), 2012. URL https://www.eia.gov/todayinenergy/detail.php?id=7590.

U.S. EIA. Short Term Energy Outlook Data Browser, 2024. URL https://www.eia.gov/outlooks/steo/data/browser/.

USGS. WaterWatch – Streamflow conditions, 2022. URL https://waterwatch.usgs.gov/index.php?id=wwdrought.

Michelle T. H. van Vliet, John R. Yearsley, Fulco Ludwig, Stefan Vögele, Dennis P. Lettenmaier, and Pavel Kabat. Vulnerability of US and European electricity supply to climate change. *Nature Climate Change*, 2(9):676–681, September 2012. ISSN 1758-6798. doi: 10.1038/nclimate1546. URL https://www.nature.com/articles/nclimate1546. Number: 9 Publisher: Nature Publishing Group.

Joshua D. Woodard and Philip Garcia, editors. *Basis Risk and Weather Hedging Effectiveness.* Seminar Paper. 2007. doi: 10.22004/ag.econ.9254.

Amir Zeighami, Jordan Kern, Andrew J. Yates, Paige Weber, and August A. Bruno.

U.S. West Coast droughts and heat waves exacerbate pollution inequality and can evade emission control policies. *Nature Communications*, 14(1):1415, March 2023. ISSN 2041-1723. doi: 10.1038/s41467-023-37080-0. URL https://www.nature.com/articles/s41467-023-37080-0. Number: 1 Publisher: Nature Publishing Group.

Jakob Zscheischler, Seth Westra, Bart J. J. M. van den Hurk, Sonia I. Seneviratne, Philip J. Ward, Andy Pitman, Amir AghaKouchak, David N. Bresch, Michael Leonard, Thomas Wahl, and Xuebin Zhang. Future climate risk from compound events. *Nature Climate Change*, 8(6):469–477, June 2018. ISSN 1758-6798. doi: 10.1038/s41558-018-0156-3. URL https://www.nature.com/articles/s41558-018-0156-3. Publisher: Nature Publishing Group.

Supplementary Materials

Note A: Post-Processing of Variable Natural Gas Prices

Variable natural gas prices are generated by the Ornstein-Uhlenbeck mean reverting model (Uhlenbeck & Ornstein, 1930) based on historical California natural gas prices. In order to factor variable natural gas prices into marginal generation costs ($/MWh), the average heat rates (MMBtu/MWh), a measure of a generator's efficiency, of PG&E's natural gas plants are multiplied by the simulated natural gas prices ($/MMBtu). Variable natural gas prices are incorporated into wholesale electricity prices by first determining which type of generator is setting the price (e.g., solar, wind, natural gas, etc.). If it's determined to be a natural gas generator, the wholesale electricity price ($/MWh) under constant natural gas prices is divided by the constant natural gas price ($/MMBtu) used by CAPOW to determine the generator's approximate marginal heat rate (MMBtu/MWh). The marginal heat rate is then multiplied by the variable natural gas price to determine the "new" wholesale electricity price under natural gas price variability.

Note B: Braun Premium

In order to price the index contracts using the Braun premium (Braun, 2016), the following simplifying assumptions are made. Peak territory is a binary variable (1 = yes; 0 = no) that represents if the contract is based in the United States. Since a majority of catastrophe risk capital is based in the United States, reinsurance based on U.S. risk does not contribute to geographically diversifying the counterparty's risk portfolio. PEAK is set to 1 for pricing the index contracts as the financial risks they manage are based in the United States. The binary variable SW (1 = yes; 0 = no) represents if the counterparty is well diversified, which can lower the premium. It is assumed that the counterparty of the index contracts will be well diversified, so this variable is set to 1. The rate on line index variable, ROLX, is a synthetic index that reflects changes in reinsurance market cycles. Baum & Characklis (2020) used the historical ROLX average over the period 1997-2012, and this value is similarly used in this work. The binary variable IG (1 = yes; 0 = no) signifies if the bond is investment grade, and this value is set to 0, since the majority of catastrophe bonds are noninvestment grade. The BBSPR variable is set to 3.5%, representing the historical average BB corporate bond spread relative to the spot Treasury curve over the last 20 years.

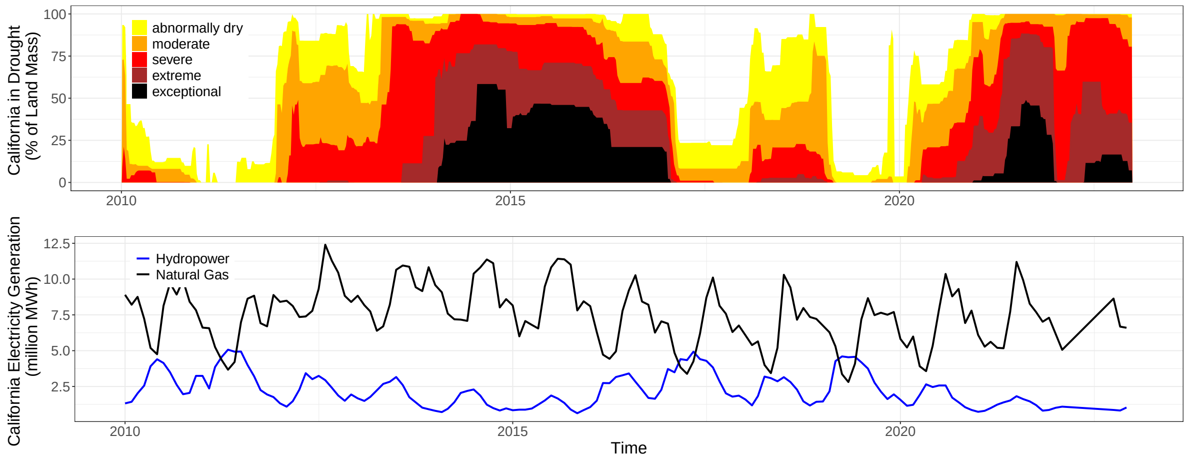

Figure S1: The historical relationship between drought (top) and California's natural gas and hydropower generation (bottom) from 2010-2022 [National Drought Mitigation Center, 2023, U.S. EIA, 2024].

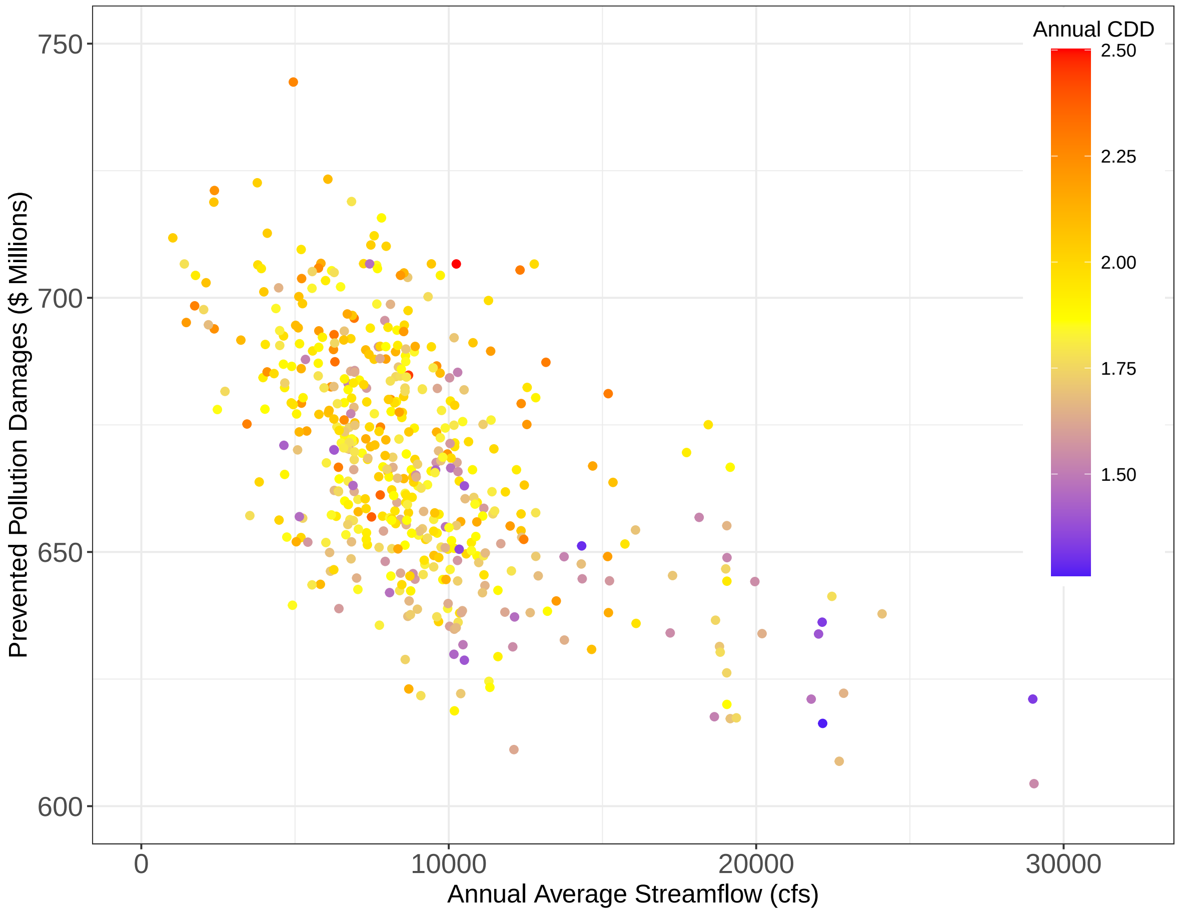

Figure S2: Prevented pollution damages (i.e. improved public health outcomes) across California versus annual streamflow within the PG&E operating domain with warmer colors representing higher annual CDD (i.e., higher summer temperatures).

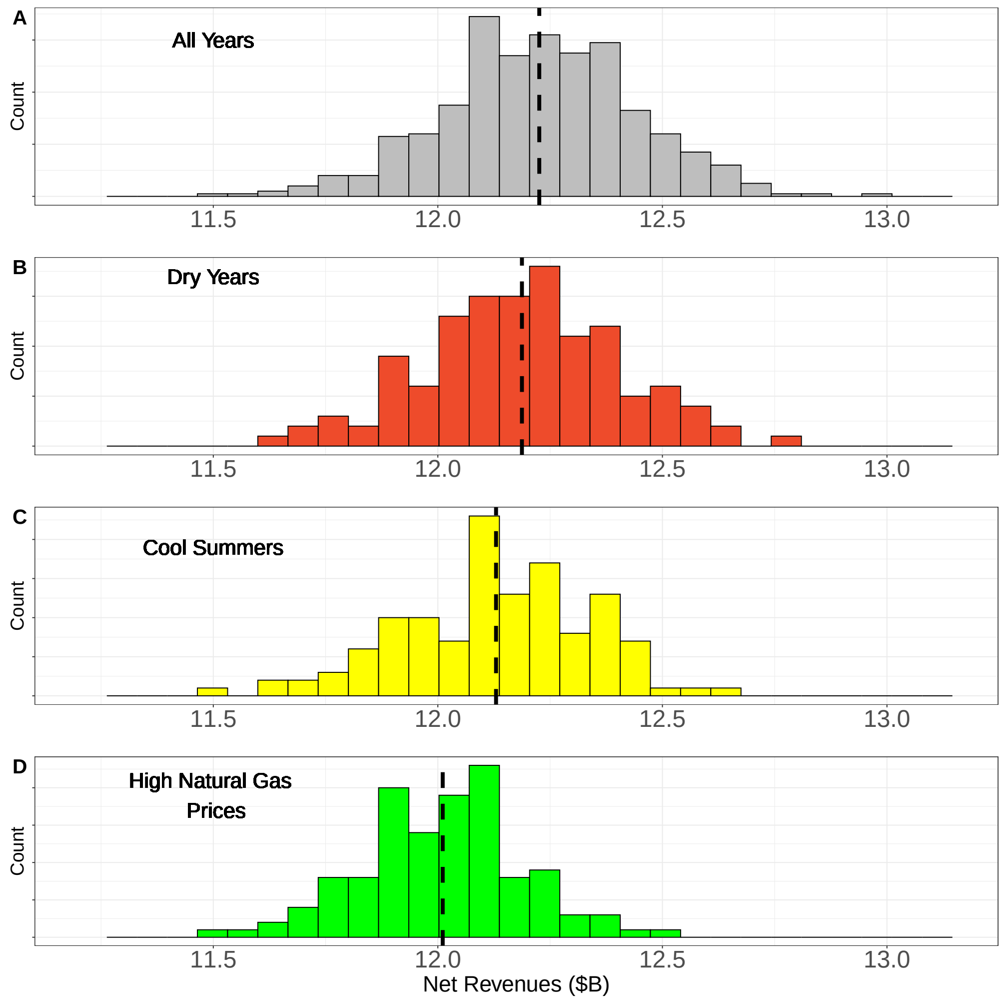

Figure S3: PG&E's annual net revenues (in $ billions) - (A) Unmanaged net revenues across the all simulation years. (B) - Unmanaged net revenues during the dry years. (C) - Unmanaged net revenues during cool summers. (D) - Unmanaged net revenues during years with high natural gas prices.

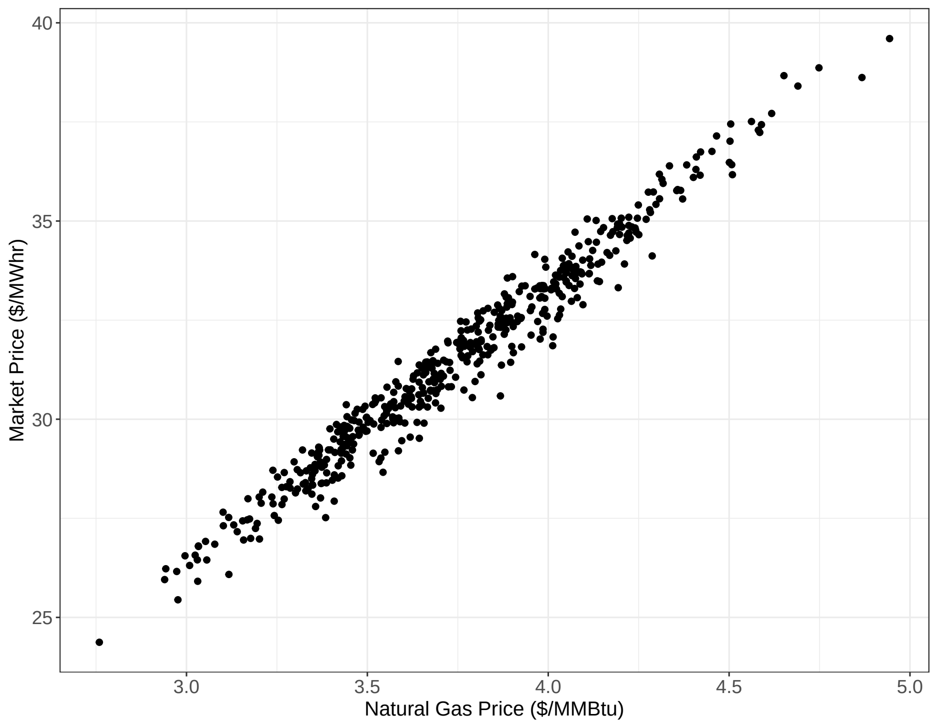

Figure S4: Correlation between Market Price ($/MWh) and Natural Gas Prices ($/MMBtu) across the simulations.

Note C: Composite Index Regression and Contract Strike Selection

Coefficients	Estimate	Standard error	p-value	Significance codes
Intercept	12.23	4.44e-03	$< 2e^{-16}$	***
Annual Streamflow	0.074	4.44e-03	$< 2e^{-16}$	***
CDD	0.108	4.46e-03	$< 2e^{-16}$	***
Natural Gas Prices	-0.161	4.43e-03	$< 2e^{-16}$	***

Table S1: **Composite Index Regression.** Output from regressing net revenues against annual streamflow, CDD and natural gas prices. The composite index is the predicted values generated using this regression. (* Significant at 0.05. **Significant at 0.01. ***Significant at 0.001).

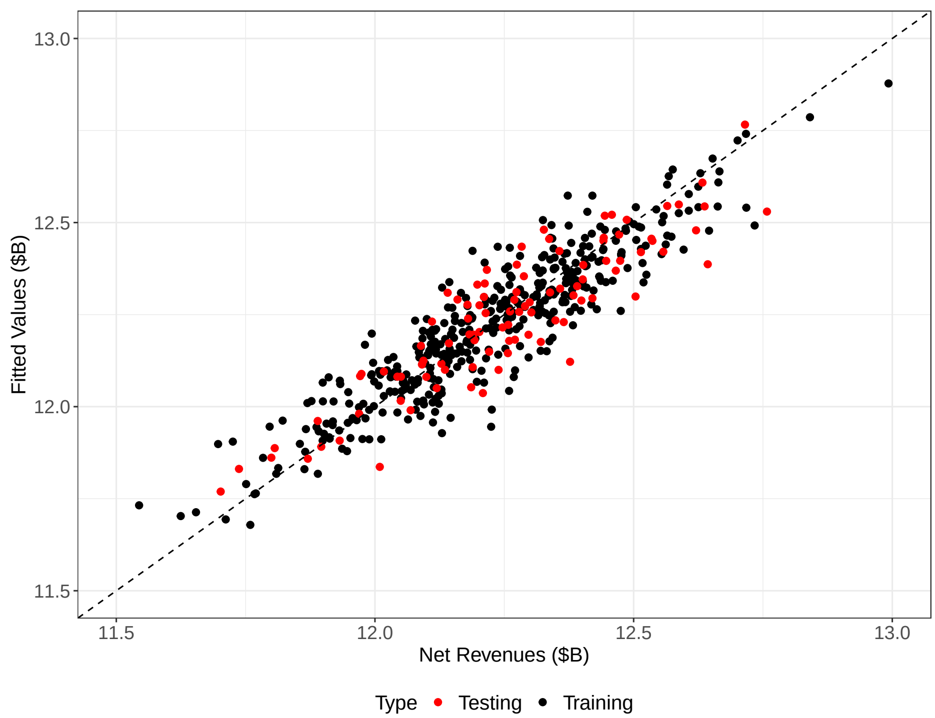

Figure S5: Scatter plot of the net revenues and fitted values. The red and black points refer to the testing and training datasets. The mean training and testing error is 7.7 and 7.8 million respectively.

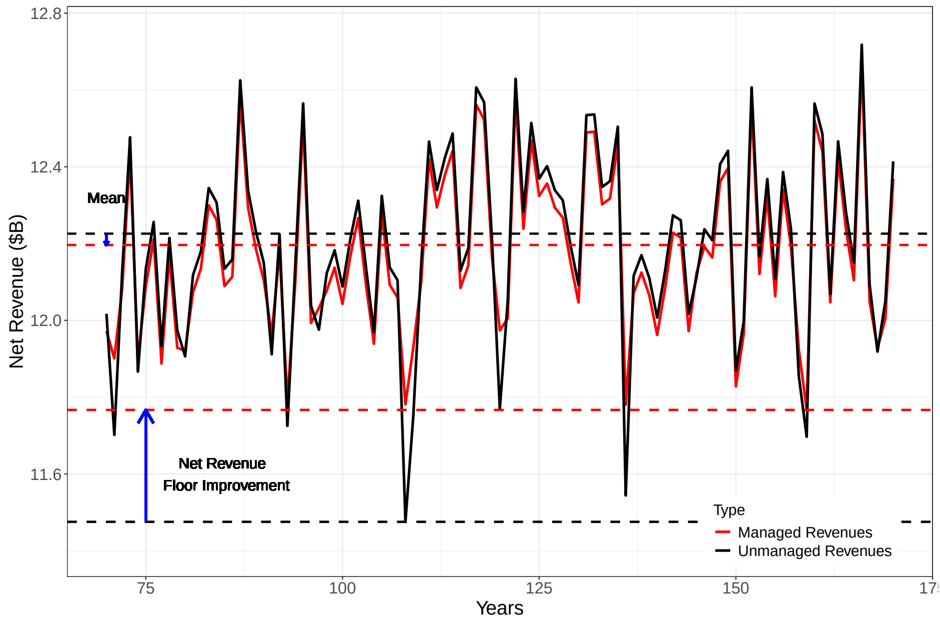

Figure S6: Simulated time series of unmanaged net revenues (in black) and those managed with the composite index contract (in red). The dotted lines at the bottom denote the minimum values (i.e. revenue floor), whereas the dotted lines at the center denote the managed and unmanaged means across all the simulation years.

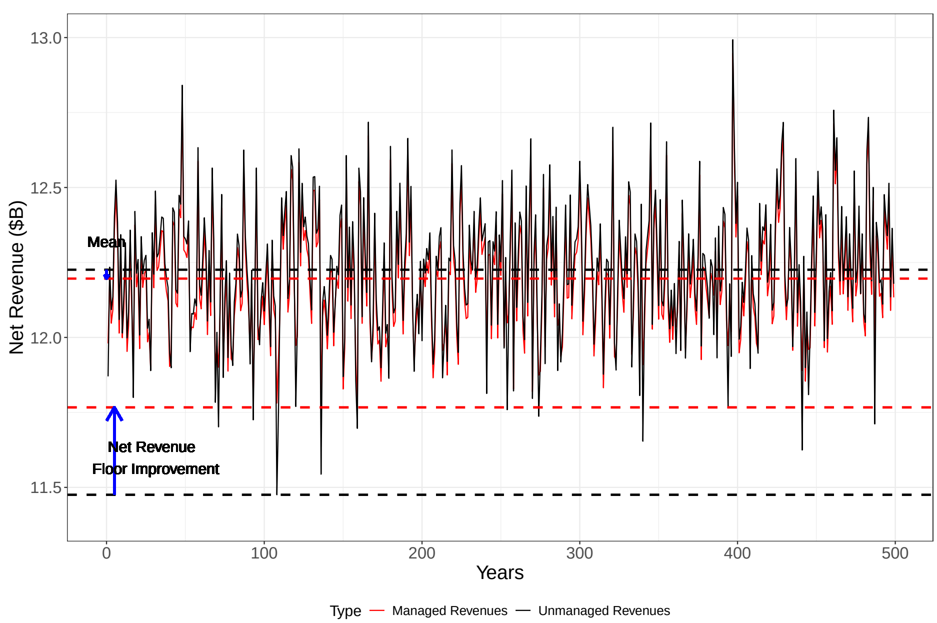

Figure S7: Simulated time series of unmanaged net revenues (in black) and those managed with the composite index contract (in red). The dotted lines at the bottom denote the minimum values, whereas the dotted lines at the center denote the mean across all the simulation years.

Setting the strike of the composite index contract to a lower value (10th percentile of the index) lowers the premium of the contract compared to higher strike as payouts are triggered less often. This also results in a smaller decrease in net revenue variance compared to using a higher strike. The choice of strike depends on the risk aversion of the utility, with higher strikes indicating more risk aversion.

Table S2: Performance of the composite index contract at different strike levels.

	Unmanaged Net Revenues	**Strike @ 10th percentile**	**Strike @ 20th percentile**
Premium ($M)	–	29.7	64.17
Expected Payout ($M)	–	9.34	23.59
Loading ($M)	–	20.39	40.58
Mean Net Revenue ($M)	12,226	12,205	12,185
Net Revenue Variance ($M)^2	47,280	40,237	33,998
Net Revenue 5th Percentile ($M)	11,870	11,892	11,928
Minimum Net Revenue ($M)	11,475	11,730	11,792

Note D: Pollution Tax Scenario and Composite Index Regression

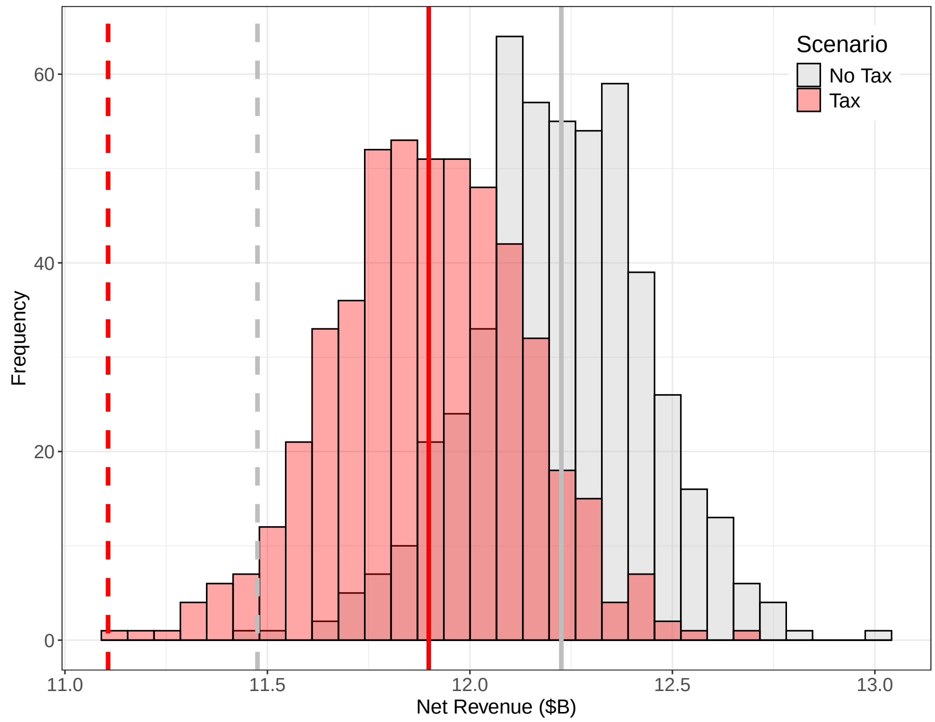

Figure S8: Influence of pollution tax on unmanaged net revenues under the no tax scenario (grey) and with the implementation of the pollution tax (pink). The red and grey lines refer to metrics corresponding to the pollution tax and no tax scenario. The solid lines denote the mean, whereas the dashed lines denote the minimum values across the simulation years.

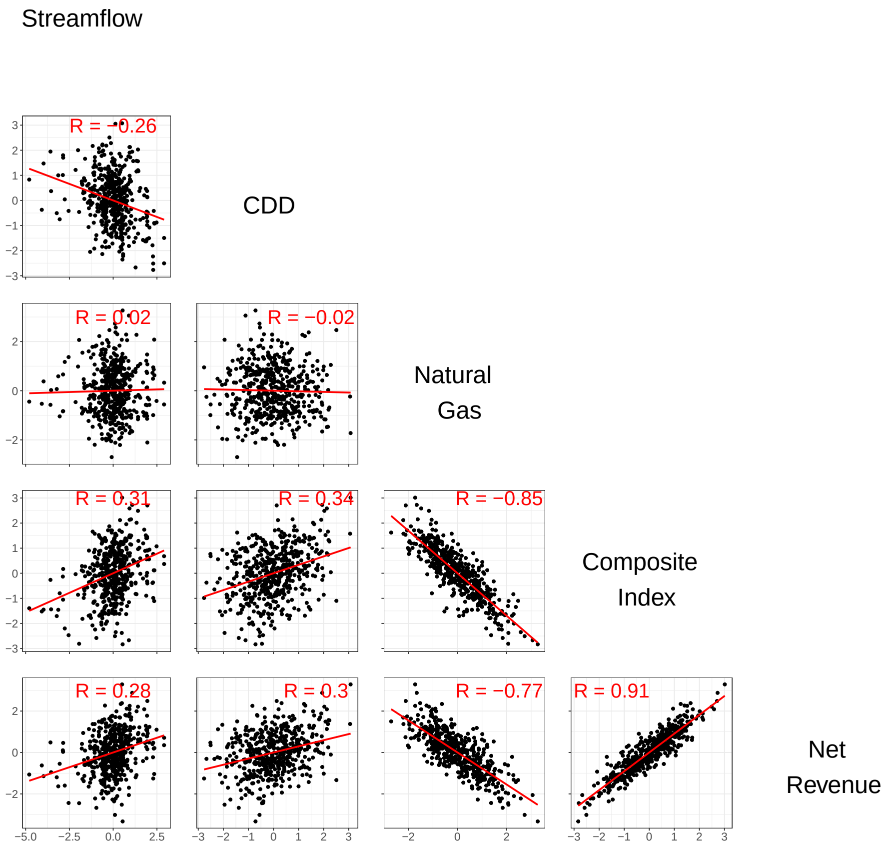

Figure S9: Correlation matrix of annual streamflow, CDD, natural gas prices, the composite index, and net revenues for the pollution tax scenario. All values are standardized. The pearson correlation coefficients for each variable pair are denoted in red within the sub-plot.

Coefficients	Estimate	Standard error	p-value	Significance codes
Intercept	11.9	5e-03	$< 2e^{-16}$	***
Annual Streamflow	0.094	5e-03	$< 2e^{-16}$	***
CDD	0.091	5e-03	$< 2e^{-16}$	***
Natural Gas Prices	-0.18	5e-03	$< 2e^{-16}$	***

Table S3: **Composite Index Regression for the Pollution Tax Scenario** Output from regressing net revenues against annual streamflow, CDD and natural gas prices. The composite index is the predicted values generated using this regression. (* Significant at 0.05. **Significant at 0.01. ***Significant at 0.001).

References

Uhlenbeck, G. E., & Ornstein, L. S. (1930). On the theory of the Brownian motion. Physical review, 36(5), 823.

Braun, A. (2016). Pricing in the primary market for cat bonds: new empirical evidence. Journal of Risk and Insurance, 83(4), 811-847.

Baum, R., & Characklis, G. W. (2020). Mitigating drought-related financial risks for water utilities via integration of risk pooling and reinsurance. Journal of Water Resources Planning and Management, 146(6), 05020007.