Dam Spillovers: The direct and indirect costs from environmental constraints on hydroelectric generation*

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Abstract

In energy markets, with several distinct production technologies, environmental regulations often do not apply equally to all firms in a market. Inter-firm interactions can cause policy impacts to spillover between producers. This research considers an environmental policy forcing hydroelectric dams to inefficiently allocate electricity generation over time. Combining quasi-random variation in regulatory stringency and a regression discontinuity design, I estimate direct costs of regulation and spillovers to other producers in the same market. These regulations increase market-wide costs as much as 19.8% and generate millions of dollars per year in pollution externalities. Spillover effects are substantial, accounting for over 50% of the true policy costs. Decomposition of spillover channels show implications for optimal policy, including allowing flexibility in the timing of regulatory compliance, as climate change continues to exacerbate water scarcity.

JEL: Q48, Q25, L51, Q52

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1 Introduction

Empirical evidence demonstrates environmental policy can have substantial impacts on the productivity of regulated firms.[1] Energy markets, in particular, often face environmental regulation but are characterized by diverse production technologies and feasible trade between regions under differing regulations. This makes it rare for producers to be uniformly regulated. Interactions between these firms can cause inefficiencies to spill over from firms under strict to more weakly regulated firms.[2] Policy analysis generally focuses on direct impacts of environmental policy on the regulated firms in spite of evidence partial regulation may spill over between firms within a given market. For example, Fowlie (2009) finds emissions leakage is quite likely from regional CO_2 abatement policies and Evans, Gilpatric, and Shimshack (2018) show enforcement actions under the Clean Water Act against one firm are transmitted through product markets and impact the behavior of other firms.

In this paper I evaluate both direct and spillover costs of environmental regulations governing the operation of hydroelectric dams in Northern California. These regulations are designed to promote diverse social goods such as flood control, wildlife habitat, fresh water supply, and recreation by bounding the allowed flow of water through hydroelectric dams.[3] Dams use this flowing water to produce electricity, so in effect, these regulations set binding minimum levels of electricity generation at hydroelectric dams which vary in stringency across time but are invariant to the social value of the electricity produced and the opportunity cost of producing it. I find the expected result that more stringent regulation reduces the value of the electricity produced by regulated dams. I also show the effects spill over to other fossil fuel-fired generators participating in the same market, leading to less efficient production decisions. In contrast to previous work examining regulatory spillovers, I observe effects at the level of the individual producer across many changes in regulatory stringency and can decompose spillover effects into allocative and productive inefficiencies. In all, between 50% and 80% of the social costs of the regulations are borne by fossil fuel producers (primarily through increased fuel consumption), emphasizing the importance of considering spillover costs when evaluating regulation.

The structure of wholesale electricity markets make them an ideal setting to examine spillovers from regulation. Markets are characterized by inelastic supply and demand, meaning small deviations from the first-best can have large impacts on costs, revenues, and welfare. Further, electricity is produced using a diverse set of technologies (*e.g.*, nuclear, coal, wind, or hydroelectric), each differing in the nature of regulations under which they are governed but producing perfectly substitutable output. These features make it likely distortions in the decisions of one firm will be communicated to the output decisions of rival firms. In Section 2, I demonstrate this mechanism for spillovers by presenting a multi-period model of a

[1] *e.g.*, Greenstone, List, and Syverson (2012) examine impacts of air quality regulations on firm productivity and Anderson and Sallee (2011) estimate costs to manufacturers of automobile fuel economy standards.

[2] *e.g.*, Duguay, Minnis, and Sutherland (2020) find changes to audit markets resulting from firms regulated by the Sarbanes-Oxley act impacted the auditing behavior of firms not required to comply with the law. Akram, Chowdhury, and Mobarak (2017) find providing transportation subsidies to transport rural laborers to areas of higher labor demand in Bangladesh also increased the wages of workers who were not offered the subsidy and chose to stay in their village.

[3] That these regulations present a net benefit to society, rising particularly from flood control and fresh water supply, is not under dispute. The goal of this paper is to characterize heretofore unaccounted costs related to the intensity of this policy on the margin, not overturn an assessment of their net social benefit.

market for electricity generation with multiple generation technologies. This model shows how constraints on the behavior of hydroelectric generators are transmitted through the output market and increase the total costs of fossil fuel generators. It makes clear predictions on the market conditions, namely the timing and degree of inelastic fossil fuel supply, which contribute to the total cost of restrictions on hydroelectric generation.

Causal identification of spillover effects in particular presents many challenges and this setting is no exception. Regulations are endogenously formed through a policy-making process with diverse and unobservable constraints and objectives. In the present setting, the stringency of the regulation increases following a schedule of discrete steps, in years when more water is available to the dams. Building on my theoretical model, Section 5 details how these structural correlations between total rainfall and requirements of the regulation confound simple estimates of the cost of these policies and could lead to large underestimates of the true policy cost. To address this challenge to identification, I leverage these repeated, discrete changes in policy stringency and a regression discontinuity design (RDD) to obtain estimates of the causal effects of regulation.

Empirical results from the RDD, detailed in Section 6, allow me to compute the magnitude of the costs and spillovers to firms. I first establish that more stringent regulations reduce the revenues hydroelectric dams earn from electricity generation between 6.0% and 7.2%, as they are constrained away from the profit-maximizing allocation of generation through time. These regulations also lead to an allocative inefficiency by requiring hydroelectric dams to discharge water and generate electricity in periods when it has low social value. Since electricity production and consumption must always balance, this causes high-cost fossil fuel generators to be called upon more often due to the inability of hydroelectric generators to offer additional supply in periods of high demand. This misallocation of hydroelectric and fossil fuel output in time increases total system costs as much as 10.4%.

Further, effects of these policies spill over to the operations of other producers, who are not directly constrained by streamflow regulations. More stringent policies create productive inefficiencies at fossil fuel generators, increasing plant-level fuel consumption between 4.6% and 16.4% per unit of electricity generated. As fossil fuel generation accounts for a larger portion of the market, between 50% and 80% of the social costs of the regulations are a result of spillovers. All told, inefficiencies resulting from these regulations impose social costs between $18.7 and $126.5 million per year in effect, or about 1.5% of the total annual cost of generating electricity.

Section 7 demonstrates these results have critical implications for both water and electricity policy. Policy evaluation which ignores spillovers to the fossil fuel sector are unlikely to correctly balance benefits and costs when determining the stringency of the policy. Castro (2019), using short-run variation in wind and solar generation, demonstrates availability of hydroelectric generation impacts the emissions benefits of those intermittent renewables. Further, while work such as Severnini (2019) show displaced hydroelectric generation under similar regulations tends to be replaced by fossil fuel generation, I find structural inefficiencies induced by the regulations increase costs and emissions more than a simple 1:1 replacement of hydroelectric generation with fossil fuel-fired sources. Following this result, I extend upon research such as Verdolini, Vona, and Popp (2018) and demonstrate the mechanisms through which intermittent renewable and hydroelectric generation assets are complements for cost-minimization. While Craig et al. (2018) find that increases in distributed renwables can decrease wholesale electricity costs in the short-run, large deployments of intermittent (*e.g.*, renewables such as wind or solar photovoltaics) or inflexible (*e.g.*, coal or nuclear) generation technologies can exacerbate the spillover effects I find here, increasing the costs of renewable portfolio standards or other generation technology mandates.

Further, while there is a substantial literature estimating the direct costs of environmental regulation (Gollop and Roberts (1983); Nelson, Tietenberg, and Donihue (1993); Mansur (2004) for electricity generation or Berman and Bui (2001) for oil refineries), little attention has been directed toward measuring the impact of spillovers to unregulated firms. A recent exception is Zhou, Bi, and Segerson (2020) which observes environmental compliance spillovers to non-participating firms' voluntary environmental programs. I exploit unique policy variation which results in repeated, discontinuous changes in the stringency of regulation to estimate substantial, positively-correlated spillovers to firms participating in the same output markets but unencumbered by these regulations. The large magnitude of spillover effects shows attention should be paid to spillovers in the analysis of regulation.

There is a recent and growing literature that examines the relationship between climate-induced water scarcity and its impacts on electricity generation, particularly through the supply of water for cooling (*e.g.*, Eyer and Wichman (2018), Lofman and Petersen (2002), Ackerman and Fisher (2013), Scanlon, Duncan, and Reedy (2013), An and Zhang (2023)). In contrast to previous literature, I am able to leverage the design of this environmental regulation to decompose costs into components attributable to water scarcity from reduced cooling water availability and lost hydroelectric generation with implications for the design of electricity markets under increasingly severe anthropogenic climate change. This is also an important input to future work following in the spirit of Fonseca et al. (2021) or Auffhammer, Baylis, and Hausman (2017) who use forward-looking simulations to examine the required increase in generation capital needed to meet electricity demand under advancing climate change.

This research leads to a number of conclusions important for the analysis of regulation in electricity markets. Previous and ongoing work have demonstrated that changes to the stock of generation capital (Davis and Hausman (2016)), level of production by specific units (Castro (2019)) or reserve requirements (Buchsbaum et al. (2021)) may have impacts on efficiency across all producers in a market. Both the theory model and empirical results demonstrate that different electricity generation technologies, while producing perfectly substitutable output, are complements in installed capacity. Increasing the deployment of intermittent renewables, as is the goal of renewable portfolio standards throughout the United States, or reducing the capacity of hydroelectric generation, as is expected under continued climate change, can lead to substantial increases in the costs from other generation technologies.

While the empirical setting of this paper is wholesale electricity markets, these results highlight that attention should be paid to regulatory spillovers in general. The theoretical model demonstrates conditions under which one should expect spillovers from partial regulation. In general, whenever a policy will cause regulated firms to alter production or reallocate it in either time or space, strategic interactions can lead to the allocative inefficiencies in both regulated and unregulated firms, as I find in this setting. Further, the empirical results find spillover costs to be more than half of the total policy costs, demonstrating regulatory spillovers can be economically significant in magnitude. These results underscore that researchers and policymakers must carefully consider spillover effects in regulatory analysis.

2 Model of the Electricity Market

In this paper I will estimate the impact of regulations on hydroelectric generators on outcomes in the electricity generation sector. The specific regulations place limits on the *minimum* level of output produced by hydroelectric dams. I describe these policies in detail in Section 3. As a prelude, it is important to understand how interactions between firms can cause these policies to spill over to unregulated firms.

I begin by presenting a two-period model of an electricity generating market containing fossil fuel and hydroelectric generators.[4] This model has two purposes, first it demonstrates how the constraints on hydroelectric generation will impact cost-minimizing decisions in the fossil fuel sector through their mutual connection in the output market. Second, it provides a platform for analyzing the impact of changing these constraints on welfare and firm profits. For the sake of brevity and clear exposition, this model makes several simplifying assumptions. A more complicated model absent these assumptions makes the same qualitative predictions and is presented in the Appendix. Further, the results presented here also generalize in an infinite horizon model, also presented in the Appendix.

2.1 Electricity supply

Consider the market for the production of electricity with two time periods $t \in \{0, 1\}$. Electricity can be generated from one of two sources: fossil fuel generators (F) and hydroelectric generators (H). In each period, the fossil fuel sector produces non-negative output (Q_t^F) with non-negative, increasing, strictly convex cost functions ($TC^F(Q_t^F)$) which are identical in each period.

Hydroelectric generators have zero marginal cost, but face a "reservoir constraint" ($\mathbb{Q}^H$) on the total quantity of hydroelectric generation (Q_t^H) available across the two periods. Additionally, a regulator exogenously sets hydroelectric "minimum generation constraints" which must be met in both periods ($Q_t^H \geq \underline{Q}^H \; \forall t$).[5] In the case that the regulator sets no minimum generation requirement, $\underline{Q}^H = 0$ serves as the non-negativity constraint on hydroelectric generation.

2.2 Electricity demand

Demand for electricity (Q_t) is exogenous and varies each period. Consistent with the reality of wholesale electricity markets, demand is perfectly inelastic in each period.[6] The social planner chooses the quantity

[4]This model will only consider the market for energy. In reality, electricity markets are more complicated and generators may be paid to provide other services such as grid reliability, often called "ancillary services".

[5]If electricity prices are greater than zero a dam will always choose to discharge water mandated by instream flow requirements through the powerhouse and produce electricity. In this light, instream flow requirements are identical to a minimum generation constraint.

[6]Wholesale electricity demand is derived from the demand of retail customers. In general, price signals from the wholesale market are not communicated to retail consumers, making demand unresponsive to wholesale prices. See *e.g.*, Puller (2002), Borenstein, Bushnell, and Wolak (2002).

of hydroelectric and fossil fuel generation each period which maximizes welfare, subject to non-negativity constraints, and that total supply equals the inelastic demand ($Q_t = Q_t^F + Q_t^H \;\forall t$). Since demand is perfectly inelastic, the welfare maximization problem is identical to the cost-minimization problem.

2.3 The social planner's problem (SPP)

The social planner observes demand for both periods and chooses the quantities of hydroelectric and fossil fuel generation in each period that minimizes total costs subject to constraints. Firms are price takers and there are no externalities in this model, thus the quantities in the optimal solution to the SPP are identical to the competitive equilibrium.

I make additional assumptions to guarantee the existence of non-trivial, interior solutions to the social planner's problem. I explain each of these assumptions in further detail in the Appendix. First, I require that the space of feasible hydroelectric output levels is non-degenerate. Second, the optimal level of fossil fuel generation is strictly positive in each period. Finally, total demand in the two periods are not identical.

Following these assumptions, the social planner's Lagrangian is:

$$\mathscr{L} = -TC_0(Q_0^F) - TC_1(Q_1^F) + \sum_{t=0}^{1} \lambda_t \cdot (Q_t^H - \underline{Q}_t^H) + \gamma \cdot \left(\bar{\mathbb{Q}}^H - \sum_{t=0}^{1} Q_t^H \right) \tag{SPP}$$

Note that the total cost functions are strictly convex, thus the negative of their sum is strictly concave. The constraints are linear (quasi-convex) in the social planner's decision variables and I assume the space of Q_t^H values satisfying the constraints is non-degenerate. Thus, this maximization problem has a unique, interior solution characterized by the first order conditions of the Lagrangian.

The Lagrange multipliers λ_t can be interpreted as the shadow cost of the minimum hydroelectric generation constraint in period t and γ is the shadow value of water in the reservoir.

The first order conditions of Equation (SPP) lead to the following useful necessary conditions for cost minimization:

$$\frac{\partial TC_0}{\partial Q_0^F} + \lambda_0 = \gamma \tag{NC.1}$$

$$\frac{\partial TC_1}{\partial Q_1^F} + \lambda_1 = \gamma \tag{NC.2}$$

$$\frac{\partial TC_0}{\partial Q_0^F} + \lambda_0 = \frac{\partial TC_1}{\partial Q_1^F} + \lambda_1 \tag{NC.3}$$

These conditions each have clear interpretation. Conditions (NC.1) and (NC.2) require, in every period, the marginal cost of fossil fuel generation is equal to the shadow cost of that period's minimum generation constraint plus the shadow cost of the hydroelectric reservoir constraint. Next, Condition (NC.3) requires the difference between the marginal cost of fossil fuel generation and the shadow cost of the minimum generation constraint must be equal across periods.

2.4 Impact of minimum generation constraints on total costs

One can also use these conditions to analyze the impact of minimum generation constraints on market outcomes using comparative statics. Consider the case where minimum hydroelectric generation constraints do not bind. The shadow costs of those constraints (λ_t) will be zero and Condition (NC.3) requires the marginal cost of fossil fuel generation must be equal across periods. This makes intuitive sense; total fossil fuel generation costs are minimized across periods when their per-period marginal costs are equal.

Now suppose the regulator exogenously increases the minimum flow constraint such that it binds in one period ($t = i$) and not in the other period ($t = j$).[7] Then the complementary slackness condition requires $\lambda_i > 0$ and $\lambda_j = 0$ and condition (NC.3) implies

$$\frac{\partial TC_i}{\partial Q_i^F} < \frac{\partial TC_j}{\partial Q_j^F} \tag{1}$$

Or the marginal cost of fossil fuel generation in period i is lower than the marginal cost in period j. Since total costs are convex it also follows that $Q_i^F < Q_j^F$ and total costs must increase over the case where the constraint doesn't bind. Thus, a binding minimum flow constraint increases total fossil fuel costs over the case where it does not bind.

These results from this model highlight the intuition of how binding minimum flow constraints on hydroelectric facilities may increase total fossil fuel generation costs. An unconstrained and cost-minimizing social planner would deploy hydroelectric generation to equalize the marginal cost of fossil fuel generation over time. Introducing a binding minimum flow constraint requires deviation from this program. The constraint requires hydroelectric generation increase in the period it binds, reducing the total quantity of fossil fuel generation and, consequently, the marginal cost of fossil fuel generation in that period. However, the reservoir constraint requires that hydroelectric generation must also decrease in the other time period, resulting in an increase in total generation costs. Convexity of the fossil fuel generation cost function requires this change in fossil fuel output will increase total costs in one period more than it decreases costs in the other.

Thus, this model of the electricity generating sector predicts any binding minimum generation requirement will necessarily increase the total cost of supplying electricity. In Appendix Section A.1.2 I further demonstrate such a constriaint will also increase the surplus earned by the fossil fuel sector if supply is more elastic in periods where the constraint binds, and have ambiguous impacts on the surplus earned by hydroelectric generators.[8]

3 Background

This paper examines the impact of environmental regulations on hydroelectric dams in the Sacramento Valley of Northern California on market outcomes for generating electricity in the NP15 electricity generating region. Maps of these regions along with locations of dams and other electricity generators are shown

[7] I show in the Appendix that such a level of the constraint must exist.

[8] In Appendix Section A.2 I demonstrate similar results under an infinite-horizon dynamic model.

in Figure 1.[9] This is a large and important market; the total costs of supplying electricity in this region have ranged from $7.4 to $12.8 billion per year over the period I consider. In this section I describe these policies governing hydroelectric dams in detail, including their motivation and specific implementation, then proceed to explain idiosyncrasies of this market which make policy spillovers likely.

3.1 Hydroelectric generation in the Sacramento Valley

The Sacramento Valley of Northern California is a hydrological region defined by the California Department of Water Resources (CADWR). Any precipitation falling in this region will flow through the tributaries of the Sacramento River into the Sacramento River Delta and then to the Pacific Ocean. This region contains the largest hydroelectric facilities in California and produces the majority of the state's hydroelectric power.

The hydroelectric dams I consider here are each backed by a reservoir which allows the dam to accumulate water over time. These dams continuously make decisions on the quantity of water to discharge from their reservoir, through their turbines for generating electricity. Once discharged, this water flows through a waterway downstream of the dam. These features of reservoir-backed dams lead to the stylized facts embodied in the model presented in Section 2: hydroelectric dams can produce electricity at effectively zero marginal accounting cost, but face a constraint on the total quantity of electricity they can produce in a given period. Thus, each unit of discharge now carries the opportunity cost of one unit of forgone discharge at some point in the future.

3.2 Environmental regulations on hydroelectric generation

The hydroelectric dams in this region face a suite of constraints on the allowed rate of downstream river flow which vary by time of year and the expected quantity of water that will be available for discharge. As described by Kosnik (2010), these constraints are the outcome of licensing decisions of the Federal Energy Regulatory Commission (FERC) and are heavily influenced by legislative and administrative policy, rather than economic optimization.[10] These constraints are formulated with diverse goals including flood management, supporting habitat for fish and wildlife, replicating natural flow rates, maintaining water supplies, and recreation.[11] Dams must follow a schedule of specified minimum rates of downstream flow which vary with the time of year and the quantity of water expected to flow through the watershed in the current year.[12] As I describe below, the design of policies governing minimum flow downstream of these dams provide an excellent setting for identifying the causal effect of these minimum flow policies on a

[9] The NP15 region is an electricity congestion zone encompassing the bulk of California north of San Luis Obispo. It contains all of the hydroelectric dams in the Sacramento Valley.

[10] Severnini (2022) examines the historical growth around dams in this region and elsewere in the United States. Importantly, the siting decisions for for most hydroelectric dams were based not only a function of the electricity generation potential, but of other water management benefits, such as flood control.

[11] Specific goals for California stream flow regulations are described in *California Water Resources Control Board Resolution No. 2010-0021*.

[12] Hydroelectric dams also face maximum flow constraints. Attaining the maximum flow rate requires a dam exceed the capacity of its turbines and discharge water through its spillways or floodgates. Such discharge decisions are not binding on the dam's decision of the quantity of electricity to produce.

number of outcomes in the electricity generation markets.[13]

For all major hydroelectric dams in the Sacramento Valley, minimum flow requirements are determined by a categorical designation of the water year type (WYT). These designations are generally "Critically Dry" (CD), "Dry" (D), "Below Normal" (BN), "Above Normal" (AN), and "Wet" (W).[14] The particular designation of the WYT is determined by an index of total unimpaired runoff from the drainage basin called the water year index (WYI). CADWR is responsible for issuing reports of measured runoff to date and a forecast of additional runoff through the end of October of that year.

The WYI is a weighted average of year-to-date and forecast end-of-year runoff in the drainage basin from these forecasts plus a lagged component as shown in Equation 2.[15] This index is updated in each month m in which CADWR updates runoff forecasts, occurring on the first Monday of February, March, April, and May, and using actual measurements on October 1. The index includes a lagged component, the final value of the WYI from the previous water year (WYI_{y-1}), to approximate the quantity of water stored in reservoirs from the previous year.

$$WYI_m = 0.4 \sum_{t=Apr}^{Jul} FLOW_t + 0.3 \sum_{t=Oct}^{Mar} FLOW_t + 0.3 \cdot WYI_{y-1} \tag{2}$$

The WYT, which in turn determines the level of minimum flow required downstream of each dam, is a step function based solely on the current value of the WYI. The rules governing determination of the WYT in the Sacramento Valley are shown in Table 1. The WYT, and minimum flow policies keyed to the WYT, change sharply at thresholds of forecast runoff. WYT designation changes five times per year after updates to the WYI and generally become binding within seven days.

As an example, the instream flow requirements downstream of the Loon Lake Dam are shown in Table 2; my research has revealed similar instream flow constraints based on the WYT in the operating licensees of other dams in the Sacramento Valley. There are some important facts to note. These minimum flow policies are categorical; minimum flows are constant within a given WYT and make discrete changes to new levels with changes in the discrete WYT.

Additionally, while minimum flows vary throughout the course of the year, in a given month they are increasing with wetter WYT categorizations. This leads to what may initially seem like a counterintuitive conclusion: as the WYI moves to "wetter" categorizations, dams face more stringent constraints on their output. These features of minimum instream flow policies are readily apparent in Figure 2, which depicts

[13]Researchers have considered these regulations in other contexts. *E.g.*, Rheinheimer, Yarnell, and Viers (2013) uses a computational model to simulate the costs of streamflow regulations in the Upper Yuba Watershed, a subset of the region I examine, with the goal of determining the level of hydroelectric generation which maximizes ecological benefits. Tanaka et al. (2011) uses a similar computational model to estimate the costs of increases in required river outflows. Both computational models account for lost revenue to hydroelectric generators but are unable to compute any spillovers to other electricity generators.

[14]Regulations covering some dams also specify an additional water year type of "Extreme Critical Dry". As described in Section 5 I identify causal effects using empirical methods that examine outcomes near thresholds for changes in the WYT which will naturally exclude observations where some dams may fall under the Extreme Critical Dry WYT.

[15]CADWR defines Sacramento River runoff as the sum of flow through the Sacramento River at Bend Bridge, Feather River inflow to Lake Oroville, Yuba River at Smartville, and American River inflow to Folsom Lake in millions of acre-feet (maf).

the required instream flows below Loon Lake Dam graphically.[16]

This relationship, that dams are more constrained in wetter years, is the source of inefficiency from these regulations and merits a brief discussion. Hydroelectric dams choose a level of electricity output by determining the volume of water allowed to flow out of the reservoir and through its turbines. Each dam has a maximum capacity to generate electricity determined by the capacity of the turbines. Unconstrained by regulation, a dam could choose any level of output between zero (allowing no water to pass) and its maximum capacity.

In this sense, a minimum flow restriction reduces the choice set of electricity production levels available to the dam. There may be cases where a profit-maximizing dam operator would choose to set flows at zero (because the price of electricity is lower than the shadow cost of the reserve constraint on water remaining in the reservoir) but is, instead forced to discharge some non-zero quantity of water due to regulation.[17] Larger instream flow requirements, occurring in wetter years, lead to smaller choice sets for the level of electricity generation at each dam. Thus, one would expect electricity supply at these dams to become more price inelastic in periods with more stringent flow requirements.

This systematic correlation between the expected quantity of water available for discharge and the stringency of instream flow policies leads to a challenge to identification of the policy impacts. As I describe in Section 5.1, a naive analysis could confound the benefits of relaxing the constraint on water reserves with the costs of tightening the constraint on instream flows. I address these challenges using a RDD on the discrete changes in instream flow policies at thresholds between each WYT.

3.3 Idiosyncrasies of electricity markets make spillovers likely

Wholesale electricity markets, such as the market in Northern California, exhibit idiosyncrasies which may lead to positively-correlated spillovers from regulation on hydroelectric generation to other producers. Foremost, while storage of electricity, *e.g.*, in batteries, is technically possible, only very recently has it become close to economically viable.[18] Proper function of the electricity grid requires supply and demand precisely balance at all times; any change in the quantity demanded must be met by a change in the quantity supplied in near real-time to avoid blackouts or damage to equipment.

Wholesale demand for electricity is derived from retail demand of end consumers and is highly variable over time. The vast majority of retail consumers during the period examined here pay a rate for electricity which does not vary over the course of the month and fails to reflect scarcity in wholesale markets.

[16] There are additional requirements of instream flow policies that are described in Appendix Section B.1. These policies likewise increase in stringency with increases in the WYT. The estimates I will present compute the cost of the full suite of instream flow policies for each WYT.

[17] Dam operators also have the option of opening floodgates and spilling water from the reservoir without allowing it to pass through the turbines. However, as long as electricity prices are above zero and discharges are below capacity of the turbines the dam operator would always be better off using discharged water to generate electricity versus spilling it.

[18] Battery storage capacity has increased substantially in California, in part due to their Public Utility Commission's implementation of AB 2514 which required 1,325 MW of investor-owned storage by 2020 with AB 2868 and SB 801 requiring additional storage investments. (See `https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/energy-storage`) As of March 2024 there were 8,434.5 MW of battery storage operating in the CAISO region compared to 7,811.1 MW in all other states combined. More than 90% of California's battery storage capacity has come online since 2020, after the sample period in this paper.

This disconnect between retail demand and wholesale prices means that wholesale demand for electricity is perfectly-inelastic and those markets use price signals to clear exclusively by adjusting supply.

Wholesale electricity markets are designed to accommodate these features. In the market operated by California Independent System Operator (CAISO) in California, generators bid supply curves into a first price auction. CAISO aggregates these bids into a single supply curve, computes a market-clearing price, and calls upon the generators with the lowest bids to produce.[19] This price-setting mechanism creates incentives for firms to bid their marginal costs and will balance supply and demand at the lowest possible cost.

In such a wholesale market, one may expect to see substantial, positively-correlated spillovers from regulations on hydroelectric dams to other market participants. First, as described in Section 2, hydroelectric generators face an opportunity cost of producing electricity. A unit of generation now removes the option to produce that unit at some other time. This reserve constraint combined with the convex costs of other generators, causes constraints on hydroelectric generation to increase the total costs of other generators.

Second, these minimum flow requirements examined require dams to discharge more water downstream making it unavailable for other uses. As noted by a number of researchers (*e.g.*, Lofman and Petersen (2002), Ackerman and Fisher (2013), Scanlon, Duncan, and Reedy (2013)) any policy reducing the availability of water for cooling at fossil fuel plants may shift electricity generation to less water-intense, but also less efficient, generating units.

In light of this, in periods when demand is increasing quickly hydroelectric dams can rapidly increase output, decreasing adjustment costs as fossil fuel generation ramps up.[20] Any operating constraints placed on hydroelectric dams will reduce their ability to alter output in response to changes in demand. This reduces the hydroelectric supply elasticity, making residual demand for fossil fuel generation less elastic. In the face of convex adjustment costs, these constraints will increase total fossil fuel generation costs, even though the regulations place no constraints on the behavior of fossil fuel generators.

4 Data

The analyses presented in this paper combine high-frequency data on electricity supply and demand with detailed information on hydrologic conditions and the state of instream flow regulations in Northern California. These data are described below with further detail and summary statistics provided in Appendix Section C.1.

4.1 Electricity markets and operations data

I have compiled data on electricity market conditions and operations in CAISO from 1997 through the present. The primary analysis is limited to the NP15 congestion zone in CAISO, which overlaps the Sacra-

[19] The actual process of market-clearing is more complicated as it must also account for, amongst other things, constraints on the transmission network.

[20] I describe attributes of various electricity generating technologies and how they may impact the total cost of electricity generation in Appendix Section B.2.

mento River Basin (see Figure 1 for a map). This includes information on the stock and characteristics of electricity generating units from EIA Form 860 and EIA "Thermoelectric cooling water data", fuel consumption and generation data from EIA Form 923, 920, and 906. Hourly operations of fossil fuel-fired electricity generators come from Continuous Emissions Monitoring System (CEMS). Finally I obtained hourly and sub-hourly prices and demands from CAISO.

The CEMS dataset only provides operations data for electricity generators reporting into the Environmental Protection Agency (EPA)'s Air Markets Program Data system. Hydroelectric dams, a critical component of the analysis in this paper, are not regulated under any air quality program and are not included in CEMS. I impute hourly operations at hydroelectric dams using information from downstream flow monitors, following Archsmith (2019).[21]

4.2 Instream flow policy data

I obtain information on historical hydrological conditions from the California Department of Water Resources (CADWR) Bulletin 120. Every February, March, April, and May the CADWR releases a forecast of total unimpaired runoff in the Sacramento Valley for the current water year. Water years start with the beginning of the rainy season on October 1 and run through September 30 of the following year. These forecasts are used to compute a numeric index of total unimpaired runoff, the WYI, and a categorical designation of the level of runoff, the WYT. No comprehensive source of contemporaneous WYI measurements or WYT designation exists. I collected contemporaneous monthly forecasts of total unimpaired runoff and observed runoff from archived copies of CADWR Bulletin 120. Using information from tables in these forecasts, I compute the numeric WYI for each monthly forecast using the formula in Equation 2 and assign the corresponding WYT in effect after that forecast. I provide a full list of reconstructed WYI values and WYT designations in Appendix Section C.2.1.

The CADWR publishes a retrospective history of official WYI values and WYT designations as of the May forecast for each water year from 1995 to the present. Table 3 compares my reconstructed value of the WYI and WYT designation to the official value in each month where data are available. In every case I correctly reconstruct the official WYT and my calculation of the WYI rounds to the official value. My reconstruction of the WYI and WYT offers two advantages over the retrospective WYI values provided by CADWR. First, minimum flow policies are based on the WYT designation computed using the most recent value of the WYI. CADWR reports past values only for the May forecasts but I am able to compute the WYI and determine the corresponding policy regime each month forecasts are issued. Second, CADWR rounds the reported WYI to the nearest 0.1, but my calculation contains approximately four significant digits. This additional precision will be important for identification of the RDD described in Section 5.1.

5 Identification

This research focuses on determining the impact of minimum flow regulations tied to each specific WYT, a treatment d on some outcome of interest Y. There are five distinct policies, one for each WYT, thus there

[21] This method is similar to, but was developed independently from Cicala (2022).

are five possible treatment states, $d \in \{CD, D, BN, AN, W\}$.

It is useful to first consider how an omnipotent researcher would design a randomized experiment to determine the effect of interest in this setting. Given free reign to set policy at-will, one could randomly assign different levels of the treatment d to each dam i and each time t then observe the outcomes. In this hypothetical, the treatment, by virtue of randomization, is uncorrelated with any potentially unobserved confounding variable and a consistent estimate of the average treatment effect of changing the policy from, *e.g.*, CD to D would be:

$$\beta_{CD,D} = E[Y_{it}|d_{it} = D] - E[Y_{it}|d_{it} = CD] \tag{3}$$

This experiment is infeasible and one must rely on observational data for empirical estimates of the effect of the policy. In such an observational context, identification of a causal effect of minimum flow restrictions on electricity market outcomes faces a number of challenges, illustrated in this context by the model presented in Section 2. Social planner's Lagrangian from that model is repeated below in Equation SPP and highlights the first challenge to causal identification addressed by this paper.

$$\mathscr{L} = -TC_0(Q_0^F) - TC_1(Q_1^F) + \sum_{t=0}^{1} \lambda_t \cdot (Q_t^H - \underline{Q}_t^H) + \gamma \cdot \left(\bar{\mathbb{Q}}^H - \sum_{t=0}^{1} Q_t^H \right) \tag{SPP.1}$$

Identification Challenge 1. Minimum flow constraints (represented by $\underline{Q}_t^H$) are, by construction, an increasing function of the quantity of water available for discharge (represented by $\bar{\mathbb{Q}}^H$) – the schedule of required discharges increases in stringency as more water is available for discharges. Additional water available for discharge relaxes the constraint on total reserves (represented by $\bar{\mathbb{Q}}^H$). This means variation in the stringency of instream flow requirements is directly coupled to variation in total reserves and the shadow cost of the reserve constraint will be correlated with the shadow cost of the minimum flow constraint, my empirical object of interest.

One could envision a simple analysis where you compare total generation costs in periods with stringent minimum flow constraints against periods where the minimum flow constraints are lax with the difference being the effect of interest. Observational variation in the instream flow constraint, however, is driven by changes in the expected quantity of water available for discharge, which also varies the level of the reserve constraint. The social planner's first order conditions (NC.1 and NC.2) show the relationship between total reserves and generation costs depend on the shape of the fossil fuel marginal cost curve and expected future demand, making a direct control for the effect of total reserves complicated. Absent an adequate control for the unobserved shadow cost of this reserve constraint, this analysis would confound the effect of the more stringent instream flow constraint with the effect of relaxing the constraint on total reserves.

Identification Challenge 2. The non-linearity of the total cost function for fossil fuel generation presents a second challenge to identification. The residual quantity of fossil fuel demand is systematically correlated with the WYI. Eyer and Wichman (2018) show water scarcity – *i.e.* a low value of the WYI – leads to less electricity generation from hydroelectric facilities and increased generation from fossil fuel generators, particularly natural gas generators.[22] Since total costs of fossil fuel generation are convex, this implies marginal fossil fuel costs will be systematically larger in years with a low value of the WYI. Failing to account for the correlation between the WYI and residual demand for fossil fuel generation could conflate effects of the policy with impacts of water scarcity unrelated to the policy.[23]

Identification Challenge 3. Finally, the hydroelectric dams governed by these constraints are not isolated. They participate in an organized market for generating and delivering electricity with other hydroelectric dams facing similar constraints and myriad other generators unencumbered by minimum flow regulations using an array of technologies to produce electricity. If the effects of regulation spill over to control units there is a violation of the stable unit treatment value assumption (SUTVA). Positive correlation between the productivity of treatment and control observations will tend to bias estimated effects toward zero. In fact, I will empirically demonstrate there are substantial, positively correlated spillovers from these regulations. Identification of the true effect of the policy on Y requires careful consideration of control observations to be sure they are uncontaminated by spillovers.

5.1 Regression discontinuity design

My preferred method of identifying policy effects relies on policy-induced discontinuities in each dam's operating constraints using a regression discontinuity design (RDD). Table 2 shows an example of how minimum flow regulations vary with respect to the WYI. At a given dam the minimum flow policies are constant with respect to the WYI until the index crosses a threshold value, shown in Table 1, at which point the required minimum flow abruptly increases.

Exploiting these discrete changes in minimum flow policies provides an attractive alternative to other empirical approaches, such as matched difference-in-differences, for identification of the causal impact of minimum flow policies. A difference-in-differences estimate could control for idiosyncratic effects using the same plant at different times as a control. While a matching algorithm could select control observations with similar values of the WYI, control observations may still be drawn from periods with systematically different values of the WYI from treated observations.[24] The RDD, in contrast, examines only observations close to the threshold for changing minimum flow policies. Identification assumes in this narrow band unobserved variables correlated with the minimum flow policy (and the WYI) are well approximated by a polynomial function of the WYI.

[22]This fact is also implied in my model by the constraint equating demand and total supply in each period.

[23]Water scarcity could bias estimates of the effect of minimum flow policies in either direction. Considering the efficiency of fossil fuel generation, a larger WYI leads to a larger portion of total electricity demand served by hydropower as opposed to fossil fuel resources. If fossil fuel units are dispatched in order of economic efficiency, the sector as a whole will appear more efficient as the WYI increases. Alternatively, abundant water means dams will need to discharge at or near their maximum capacity more often to manage the level of their reservoirs. This will lead to a price-inelastic supply of hydropower which may increase the cycling of fossil fuel generation, leading to lower system-wide efficiency. Overall, it appears fossil fuel generation is more efficient with larger values of the WYI.

[24]For example, Eyer and Wichman (2018) show water scarcity, which varies systematically with the WYI, leads to increased demand for fossil fuel generation.

In the spirit of Hahn, Todd, and Van der Klaauw (2001), my primary estimating equation for the plant-level effect of moving from instream flow policy A to polcy B using the RDD is

$$Y_{it} = \beta^{AB} \cdot d_t^{AB} + f^{AB}(WYI_t, d_t^{AB}) + \mathbf{\Gamma_i^{AB}} + \mathbf{\Xi_m^{AB}} + \varepsilon_{it} \tag{4}$$

Where Y_{it} is the outcome of interest, d_t is an indicator for treatment set to zero for observations under policy A and one for observations under policy B. To account for the fact that outcomes may vary with the quantity of water available for discharge, $f(\cdot)$ is a flexible polynomial in the WYI, with all parameters estimated separately on each side of the discontinuity. Following the suggestion in Gelman and Imbens (2019), my preferred estimates specify $f(\cdot)$ is a local linear trend using the triangle kernel over the desired bandwidth. $_{\mathbf{i}}$ is a vector of plant-level fixed effects and $_{\mathbf{m}}$ are month-of-year fixed effects. I estimate the model parameters for each policy separately; the treatment effects, polynomial trends in the WYI, and fixed effects have separate values for each potential policy change A, B. This idiosyncratic error term ε_{it} may be correlated within plants and within months and I compute test statistics robust to arbitrary heteroskedasticity and correlation within plants and within months using the two-way clustering procedure described in Cameron and Miller (2015).

With some outcomes of interest, for example the system-wide total cost of electricity generation, there is a single observation per time period and no cross-sectional dimension. In these cases, my estimating equation excludes the cross-sectional dimension and fixed effects, becoming:

$$Y_t = \beta^{AB} d_t^{AB} + f^{AB}(WYI_t, d_t^{AB}) + \mathbf{\Xi_m^{AB}} + \varepsilon_t \tag{5}$$

Again, $f(\cdot)$ is a local linear trend in my preferred specification. The idiosyncratic error may be correlated within months and I compute test statistics robust to arbitrary heteroskedasticity and correlation within months.

In this setting an RDD resolves the challenges to identification described above with minimal assumptions. First, the RDD estimates treatment effects using only observations with WYI values that are close to each policy threshold, with "treated" observations having WYI values in excess of the threshold and "control" observations below the threshold. Identification Challenge 1 stems from an omitted variable affecting the outcome that is correlated with treatment – the shadow value of water is correlated with the WYI and, hence, the WYT. In using observations with values of the WYI close to the threshold, the RDD selects treatment and control observations that are similar on unobservables and where the omitted variable is plausibly accounted for by a linear control in the WYI.

Similarly, Identification Challenge 2 embodies the fact that fossil fuel generation (and total costs) will be systematically larger when the WYI is lower. Since total fossil fuel costs are convex, it may be difficult to adequately control for variation in total fossil fuel costs related to water scarcity but unrelated to instream flow requirements. Here again, by selecting observations close to a threshold between a change in instream flow policies, the total quantity of water available for discharge is similar across treated and control observations and variation in fossil fuel costs are well-approximated by a linear trend.

The RDD also provides a satisfying solution the Identification Challenge 3. Treated and control units are drawn from the same pool of observations where values of the WYI are close to a policy threshold. In this narrow range around a policy threshold, the fact that WYI for a particular observation is above (treated) or below (control) the threshold is a function of past precipitation and future forecasts and likely uncorrelated with treatment status of other observations close to the threshold, satisfying the SUTVA assumption.[25]

The RDD provides many attractive attributes for causal identification in this setting. These benefits come with limits to interpretation which merit discussion. As identification of the causal effect of a policy comes from outcomes with a WYI value close to the critical value of the WYI where the policy changes from one WYT to the next, the estimates are a local average treatment effect of the schedule of flow policies under one WYT compared to the next-less restrictive WYT. For example, I am able to estimate the additional impact of moving from the D policy to the BN policy, a policy change I will term D→BN, by comparing outcomes where the WYI is just above the policy threshold between these policies against outcomes where the WYI is just below the policy threshold. This provides a credible impact of the effect of the policy on the outcome as the policy currently exists, however, since outcomes may vary systematically with values of the WYI, these estimates offer little insight to the counterfactual outcomes if, *e.g.*, the policy thresholds were set to different levels of the WYI.[26] Additionally, as I never observe outcomes in a world without regulation, I cannot compute the full effects of regulation (compared to the absence of regulation) without additional structural assumptions.

5.2 Calculation of the counterfactual benchmark

My empirical estimates are based on data spanning from 1998 to the present. During this period there was substantial growth in electricity demand and generating capacity, and a significant shift in the mix of technologies used for electricity generation. To account for these changes in electricity supply in a consistent manner, I compare each outcome of interest to a counterfactual benchmark. In this benchmark, I reallocate hydroelectric output, ignoring instream flow requirements, to optimize some criterion – generally minimizing total electricity generation costs.[27] For each observation, I then compute how close the observed value of the outcome is to the benchmark.[28]

For each set of empirical estimates, I collect hourly data for 28-day windows starting on the second Monday of each month.[29] I then compute a counterfactual by reallocating hydroelectric generation to minimize costs given *ex post* realizations of demand and the marginal cost curve. The couterfactual

[25]While the treatment/control status of an observation should not be correlated with outcomes of another observation, my empirical specifications perform inference clustering by water year to allow for any serial correlation between observations.

[26]For example, Null and Viers (2013) contemplates the possibility that continuing climate change may necessitate changing the WYI thresholds for each WYT as the distribution of WYI values changes over time.

[27]In the examples that follow I will treat total generation cost minimization as the objective. However, there are other objectives that could be used for reallocating hydroelectric output, *e.g.*, maximizing firm revenue.

[28]Clearly, this benchmark represents an allocation of hydroelectric output that cannot be practically attained; however, it provides a consistent reference for total electricity generation costs absent instream flow constraints. This is conceptually similar to the benchmark of a fully unconstrained electrical grid in Cicala (2022).

[29]In the months of February, March, April and May the CADWR issues an updated Bulletin 120 on the first Monday of the month. This report details water year-to-date stream flows and forecast future flows in the Sacramento Valley which are used to compute the current value of the WYI and WYT. Updated instream flow policies generally become binding seven days later.

reallocation satisfies constraints requiring that hydroelectric and fossil fuel output be non-negative, hydroelectric output is less than or equal to the nameplate capacity of all hydroelectric dams for which I have hourly output data, and the total quantity of hydroelectric generation over the 28-day window must equal actual hydroelectric generation.

This method of reallocating hydroelectric output in the counterfactual forms a benchmark for comparison of total costs under different realizations of instream flow policies with desirable properties. Namely, a welfare-maximizing social planner would solve a dynamic optimization problem, allocating hydroelectric output when the marginal cost of other sources are high and withholding output when marginal costs are low subject to a constraint of the total water available in the reservoir. If the social planner at some point in time chooses a level of output below the maximum, there is a shadow value on each unit of water discharged by the dam.

By holding total discharges constant, the counterfactual requires that the quantity of water in the reservoir at the start and end of the counterfactual period be identical to the observed values. If, after the end of the counterfactual period, policies revert to those I observe in the real world, the state, value functions, and continuation value of the social planner's optimization problem are identical to those observed in the real world.[30] This implies the shadow value of water in the reservoir will be identical as well.

This has some straightforward implications for my counterfactuals and the interpretation of the results that follow. First, analyses relying on a counterfactual reallocation of hydroelectric output capture the treatment effect of changing instream flow policies for the period of the 28-day window and then reverting to the realized policies. Second, by construction the shadow value of water is identical at the end of the counterfactual to the realized shadow value. A cost-minimizing social planner could do no worse by optimally reallocating water over even longer horizons. Thus, the counterfactual reallocation is a lower bound on the true *ex post* optimal reallocation of hydroelectric generation over time.

6 Results

I now turn to my primary estimates of the impact of minimum flow policies on electricity market outcomes for both hydroelectric dams and fossil fuel generators using the RDD and the policy discontinuities described in Section 5.1.[31]

A threat to obtaining causal estimates from a RDD is manipulation of the running variable. Here, the running variable is a function of forecast precipitation in the Sacramento River Basin. It would be highly impractical for some agent to manipulate precipitation in order alter the WYT classification. However, it is possible forecasters could be influenced to alter forecasts in a way that leads to a particular WYT designation. Figure 3 shows a histogram of WYI values over the full sample. Empirical tests of running variable manipulation proposed by McCrary (2008) and Calonico, Matias D Cattaneo, et al. (2019) fail to

[30]This is consistent with conditions I derive from an infinite-horizon discrete time model of a cost-minimizing social planner in the Appendix.

[31]I compute RDD estimates and perform robust inference following Calonico, Matias D Cattaneo, et al. (2019) using Stata code derived from Calonico, Matias D. Cattaneo, and Farrell (2016). When the data allow, I use the procedure to compute data-driven bandwidths described in Imbens and Kalyanaraman (2012) using Stata code from Kaiser (2014).

reject the null hypothesis of no running variable manipulation. Details of these tests are provided in Appendix Section D.3.

Looking at the histogram of WYI values in Figure 3 it is clear there is little density in the vicinity of the threshold between "Above Average" and "Wet" WYT categories. This is borne out in the RDD estimates and I am generally unable to estimate treatment effects in the vicinity of this policy threshold for any reasonable choice of bandwidth. Consequently, in the analyses that follow, I exclude this policy threshold from my analysis and instead focus on the remaining three policy thresholds.

6.1 Impact of instream flow policies on total costs of fossil fuel generation

The shadow cost of the reservoir constraint on hydroelectric generation is near constant in the short-run. As outlined by the model in Section 2, a cost-minimizing social planner would allocate hydroelectric generation over time so that hydroelectric output is the highest when the marginal cost of other generation sources, typically fossil fuel generation, is high and withhold hydroelectric generation when the marginal cost of other generation sources is low.

The event study in Appendix Section D.2 shows minimum flow policies alter the discharge behavior of hydroelectric dams. One would expect binding constraints on hydroelectric generation to create an allocative inefficiency in electricity generation. Dams are forced to discharge water and generate electricity in periods when the marginal cost of displaced generation is low, leaving less water available for discharge when the marginal cost of electricity from other sources is high.

A first-order question is how instream flow policies affect the total cost of fossil fuel generation. This is an inherently complicated question. Electricity in California is supplied by a fleet of merchant and regulated generators, and there is no centralized accounting of costs. Additionally, hydroelectric generation can account for as much as 22% of total consumption. A counterfactual reallocation of hydroelectric generation can substantially shift residual demand for fossil fuel generation. Simply knowing the marginal cost in any hour is insufficient for computing counterfactual costs under large reallocations of hydroelectric output. I address this challenge by computing the total cost of fossil fuel generation using a simulated supply curve for fossil fuel generation.

In each month of the year, I compute the marginal fuel cost per MW of each fossil fuel generating unit operating in the CAMEX eGRID subregion, which is essentially identical to the footprint of the CAISO.[32] One could then construct a supply curve by rank-ordering plants according to their marginal costs. Fossil fuel generating units, however, can be unreliable and should not contribute to the supply curve when down for maintenance or otherwise unable to produce electricity. No comprehensive source of power plant outages is available. As an alternative, I compute mean forced outage factors for plants based on the primary fuel and generation technology from the National Electricity Reliability Council's (NERC) Generating Unit Statistical Brochure using a method similar to Borenstein, Bushnell, and Wolak (2002). I then compute the supply curve as the mean of 1,000 Monte Carlo simulations of the rank-ordered supply curve where fossil fuel units are unavailable at rates determined by their forced outage factor.

[32] I compute the fuel cost per MW as the price of fuel purchased by the plant, from EIA-903/923, and the plant's heat rate from CEMS.

Demand for electricity is near-perfectly inelastic. For each hour I compute realized fossil fuel load as the sum of all electricity supplied by fossil fuel generators in that hour. Intersecting this perfectly inelastic residual demand for fossil fuel generation with the simulated supply curve gives an expected marginal cost of fossil fuel generation in each hour. Expected total generation costs are the integral of this supply curve from zero to the residual fossil fuel demand.

Following the method of constructing a counterfactual described in Section 5.2, I compute a benchmark of the cost-minimizing allocation of hydroelectric generation, transferring hydroelectric output from the hours of lowest marginal fossil fuel generating cost to those of highest marginal cost.[33] I assume all counterfactual changes in hydroelectric output are absorbed one-for-one by fossil fuel generators, shifting counterfactual fossil fuel demand accordingly. I compute the total cost of fossil fuel generation, both realized and counterfactual, by integrating under the supply curve up to the quantity demanded.

My calculation of the change in costs realized by optimal reallocation of hydroelectric output is illustrated in Figure 4. The upward-sloping curve represents the fossil fuel supply curve for that month, computed using the Monte Carlo simulation described above. In each panel, the line labeled "Realized" is the realized residual demand for fossil fuel generation in a given hour. Panel (a) shows an hour where total costs are reduced by increasing hydroelectric generation, offsetting the need for some high marginal cost fossil fuel generation.[34] The line labeled "Optimal" shows the counterfactual demand for fossil fuel generation. The shaded area in between is the total reduction in fossil fuel generation costs achieved in this hour by optimal reallocation of hydroelectric generation.

Increasing hydroelectric output can reduce costs in that hour, but comes with a price: there is less water is available for discharge in some other period. Panel (b) shows the same graph for a different hour where hydroelectric generation is decreased. This raises total fossil fuel generation costs in that hour by the amount in the shaded area. From these graphs it is clear how the reallocation of hydroelectric generation decreases costs. The increase in hydroelectric generation in Panel (a) is nearly identical in magnitude to the decrease in Panel (b). However, the total cost reduction in Panel (a) is much larger than the total cost increase in Panel (b). This process reallocates hydroelectric discharges, respecting non-negativity and capacity constraints, from periods of low marginal cost to periods of high marginal cost, across a 28-day window to the total cost-minimizing allocation of hydroelectric generation.

I compute the ratio of realized to optimal total fossil fuel generation costs for four-week windows starting with the second Monday in each month.[35] I then estimate the effect of instream flow policies on this ratio using the RDD framework from Section 5.1. These represent the percentage increase in costs relative to perfect cost-minimization. A scatter plot of the the ratio of realized total generation costs to the

[33]Since generators are assumed to have constant marginal cost, there are portions of the supply curve that are flat and the solution to the cost minimization problem may not be unique. My minimization algorithm makes total cost-reducing reallocations of hydroelectric generation, subject to non-negativity and capacity constraints, until no additional reallocations can be made, finding one of potentially many cost-minimizing allocations.

[34]As described in Section 5.2, I require total hydroelectric generation over the course of each 4-week period to be identical to actual generation. So the increase in hydroelectric generation in this hour, with high marginal fossil fuel cost, is made possible by corresponding decreases in some other hours with lower marginal fossil fuel costs.

[35]CADWR forecasts, and associated WYI and WYT designations are issued on the first Monday of February, March, April, and May and become binding seven days later.

optimal benchmark in the vicinity of each policy threshold are shown in Figure 5.

It is important to note, since total costs are computed using a constant supply curve in each month, these estimates capture changes in total generating costs assuming zero adjustment costs across all fossil fuel units. If it is costly to adjust fossil fuel output, these estimates represent a lower bound on the costs of minimum instream flow policies.[36] I present estimates in Section 6.3 which capture adjustment costs at the plant-level.

The estimates for a range of bandwidths are shown in Table 4. The CD→D policy has precisely-estimated zero effects on total costs. The D→BN policy leads to increased generation costs on the order of 9% to 10%. There is weak evidence on small increases in total costs from the BN→AN policy.

These results are broadly consistent with the hypothesis that instream flow regulations can cause hydroelectric generators to misallocate discharges over time. Instream flow requirements under both the CD and D policy are small and likely force little misallocation. As flow requirements become larger under the BN policy, dams are forced to discharge larger quantities of water when fossil fuel generation costs are low. Further, in periods governed by the BN policy, water is still scarce and required discharges carry the opportunity cost that dams may need to allocate output away from periods when fossil fuel costs are the highest. As water becomes more plentiful under the AN policy, minimum flow requirements become less binding on the decision of dams to discharge at or near capacity when fossil fuel generation costs are high.

6.2 Impact of minimum flow policies on hydroelectric generation revenues

The model in Section 2 demonstrates the change in hydroelectric revenues from increasing the stringency of instream flow requirements is ambiguous, both in sign and magnitude, and depends on the elasticity of fossil fuel supply and allocation of hydroelectric output.

Here I consider the impact of instream flow policies on the revenues earned by hydroelectric generators. For each hydroelectric dam, I compute the ratio of actual revenues (computed as the sum of hourly nodal prices time the quantity of electricity produced) divided by counterfactual revenues had the dam produced the same quantity of electricity allocated to the hours of the highest prices, subject to its production constraint. The fact that offer curves at the nodal level are not available from CAISO presents an additional limitation of this analysis. Absent information on the aggregated bid curve, I am unable to compute counterfactual prices as dams adjust their output. Here I assume perfectly elastic supply by non-hydroelectric generators, so reallocation of hydroelectric generation has no effect on prices. Scatter plots of the ratio of realized hydroelectric dam revenues compared to the optimal benchmark are shown in Figure 6.

Note that these estimates speak little to the welfare impacts of instream flow policies, but only to the incidence of the policy. Since demand for electricity is near perfectly inelastic, lost revenues by hydroelectric generators represent transfers between consumers and various generators and may have minimal

[36] Since my simulated supply curve is weakly increasing in load, the algorithm for the counterfactual reshuffles hydroelectric output from periods of low residual fossil fuel demand (and low marginal costs) to periods of high fossil fuel demand (and high marginal costs). This reshuffling, by construction, reduces the hour-to-hour variability in the residual demand for fossil fuel generation and would reduce adjustment costs. Accounting for adjustment costs would likely lead to additional cost-reducing reshuffling of hydroelectric output, making my counterfactual a lower bound on total cost reductions.

impact on total surplus.

In Table 5, I compute the effect of changes in flow regimes tied to the WYT on the ratio of revenues from electricity generation by each hydroelectric dam to the *ex post* optimal value for discharging the same quantity of water using the RDD framework described in Section 5.1. Effects of the D→BN policy are poorly estimated, but all policies appear to cause dams to discharge in ways that reduce profits. Revenues at affected dams are reduced between 6.6% and 7.2% compared to the *ex post* optimal value.

6.3 Impact of minimum flow policies on fossil fuel generation efficiency

As described in Section 3.3, efficiency losses stemming from operational constraints on hydroelectric facilities may spill over into other forms of electricity generation as well. For example hydroelectric generation, due the ability to near costlessly and instantaneously adjust output, can smooth out short-term changes in the residual demand faced by fossil fuel generation, thereby reducing adjustment costs and lowering overall system costs. Regulations which reduce the ability to adjust output will diminish this damping effect and tend to raise overall system costs.

The analysis in Section 6.1 computes the system-wide increase in fossil fuel generation costs assuming a static supply curve from hour-to-hour. Those estimates are unable to account for changes in within-plant efficiency resulting from instream flow policies. Namely, changes in variability of residual demand may lead to additional cycling of individual fossil fuel generators and increase plant-level adjustment costs. Further, policy-induced restrictions on water availability could cause fossil fuel plants using surface water for cooling to make operation decisions which reduce their water intensity but cause them to be less efficient converting fuels into electricity.

This leads to a central question – do flow regulations on hydroelectric facilities cause individual fossil fuel generators to operate less efficiently? One such measure of operational efficiency in fossil fuel generation is the heat rate.[37] Similar to the analysis of instream flow policies on total generation costs, I aggregate the mean heat rate over all fossil fuel generators for 28-day periods starting on the second Monday of each month.

The composition of the fossil fuel plants called upon in each month may vary in ways that are correlated with the total demand for electricity.[38] Further, allowing between and within-plant variation would capture some of the same effects of the allocative inefficiency estimated above. To account for these facts, I aggregate across plants using the quantity-weighted mean deviations from plant-specific average heat rates as the measure of plant efficiency in this analysis.

I investigate the impact of minimum flow restrictions using the aforementioned RDD. For each WYT, I estimate impact of moving to the next-most restrictive WYT on the above measure of plant efficiency. The results are shown in Table 6 for a range of feasible bandwidths.[39] Moving from minimum flow policies

[37]Numerous analyses of electricity markets rely on heat rates as a measure of generation efficiency, for example Fabrizio, Rose, and Wolfram (2007) and Bushnell, Mansur, and Saravia (2008).

[38]Given an upward-sloping supply curve, one would expect inefficient plants to be called on more often in months with high demand.

[39]The local linear regressions underling the RDD require two distinct values of the WYI on each side of the discontinuity, setting a lower bound on the feasible bandwidth for each policy threshold. When possible I have computed asymptoticly square

in the “Critical Dry” WYT to the “Dry” WYT increases fuel consumed to generate one unit of electricity by 4.6% to 5.1%. Flow restrictions associated with “Above Normal” WTY increase fuel consumption between 4.2% and 14.7%. The “Below Normal” minimum flow restrictions increase fuel consumption between 5.9% and 15.9% but the effects are not significant for large bandwidths.

These results are presented graphically in Figure 7. Each panel shows a Lowess-style plot of the heat rate deviations as a function of the WYI. A solid black line represents the policy discontinuity. These plots broadly demonstrate an important concern for identification in this context. While heat rates tend to decline as the WYI increases, they sharply increase when the WYI crosses a policy threshold. Empirical analyses failing to account for the general downward trend in heat rate as a function of WYI will tend to understate the impact of the policy on thermal efficiency of electricity generation.

6.4 Placebo test

As described in Section 5.1, the RDD estimates are attractive for causal identification of the impact of minimum stream flow regulations on the efficiency of electricity generation. While RDDs simulate many attributes of the gold-standard randomized control trial in the vicinity of the policy discontinuity, an RDD is still not an RCT. As evidence the estimates from my primary RDD are not driven by some underlying, systematic trend in the data unrelated to the minimum flow policy itself, I conduct a “placebo test” where I repeat the specification of my primary RDD, keeping the treatment intact, but changing to an outcome where one would expect to see zero treatment effect.

Implementing such a placebo test, I replace the outcomes in my analysis, the hourly system-wide heat rate of fossil fuel electricity generation, with outcomes from a disconnected market lacking the same policies regulating the minimum flow on hydroelectric facilities. Specifically, I construct a measure of system-wide heat rates for generation in the Electric Reliability Council of Texas (ERCOT) using identical methods I use for the NP15 region of CAISO in my primary specification.[40] One would expect the minimum flow regulations to have no effect on the efficiency of generation in disconnected markets. Figure 8 shows these results graphically. Across the range of bandwidths from my primary specification the estimated effect of Northern California’s minimum flow policies are precisely estimated, very close to zero, and generally statistically insignificant.

6.5 Policy total costs

The estimated impacts of these policies are substantial. Table 7 breaks down the estimated annual cost in electricity generation of each set of minimum flow policies. Inefficiencies resulting from the misallocation

error loss-minimizing bandwidths using cross-validation and the method described in Imbens and Kalyanaraman (2012). These automated procedures generally select bandwidths in the narrow end of the feasible range.

[40]ERCOT is an independent system operator responsible for balancing electricity supply and demand in a region covering most of the state of Texas. As of 2016 CAISO and ERCOT operate on separate electricity interconnections defined by the North American Electric Reliability Council (NERC) and no major transmission lines connect these regions. The ERCOT and NP15 region of CAISO are effectively disconnected markets. Furthermore, the EIA reports less than 0.1% of electricity generated in ERCOT in 2014 was generated by hydroelectric facilities. Even if precipitation is geographically correlated between the Sacramento Valley and Texas, availability of water for hydroelectric generation is likely not to be an issue in the ERCOT region.

of hydroelectric generation over time raise the total cost of fossil fuel generation between \$0.5 and \$47.4 million per year. However, productive inefficiencies at fossil fuel plants resulting from instream flow policies are substantial, ranging from \$13.86 to \$52.58 million per year. Including damages from the additional greenhouse gas (GHG) and local criteria pollutant emissions, the bulk of the cost of these policies are the result of spillovers into and externalities from fossil fuel generation.[41]

6.6 Other policy costs and benefits

The costs of these policies, in particular the spillovers of regulation of instream flows to the efficiency of fossil fuel generation, are the primary focus of this research. It is, however, important to frame these costs to electricity generation against other potential costs and benefits of instream flow policies. Unfortunately, while the high resolution of policy changes and data provide a platform for detailed analysis on the impacts on electricity generation, the same cannot be said for data illuminating other potential costs and benefits of instream flow policies. Economic data, for example, on consumer valuations of water-related recreation activities have at best annual resolution and may span multiple policy changes.

6.6.1 Other policy costs

There are some investigations of other costs of instream flow policies. Tanaka et al. (2011) model economic outcomes as a function of outflows from the Sacramento River Delta into the Pacific Ocean using the CALVIN model.[42] While this analysis provides an estimate of some costs of these policies, it is admittedly unsatisfactory for welfare accounting. Namely, the marginal costs of additional Delta outflows computed by CALVIN do not account for contemporaneous water scarcity. Water is clearly more valuable on the margin in dry years than in wet years.

In spite of these shortcomings, I use estimates from Tanaka et al. (2011) to compute estimate costs of each suite of flow policies on Delta outflows. These costs are divided into agricultural, water used to maintain instream flow rates cannot be deployed for agricultural use, and environmental, rather than discharge to the Delta, water could be used to maintain upstream riparian ecosystems. Estimates of these costs are shown in Table 8. In general, total costs to environmental and agricultural uses are of similar magnitude to the estimated costs in electricity generation.

6.6.2 Policy benefits

Instream flow policies provide many social benefits as well. Stated goals of these policies include flood management, supporting habitats for fish and wildlife, replicating natural flow rates, maintaining water supplies and support of recreation activities. As with non-electricity costs, data valuing these benefits are sparse and direct estimation of the incremental benefit of instream flow policies is not possible given the

[41] I compute changes in GHG and local criteria pollutants using the same RDD specification and compute damages using spatially disaggregated marginal damages from Muller (2014). Details are provided in Appendix Section D.5.

[42] The CALVIN model is an economic-engineering optimization model of California water systems used to model water policy, operations, and planning problems.

available data. Instead, for a frame of comparison, I have compiled data on the total consumer valuation of some of these purported benefits.

Table 9 summarizes economic activity associated with the recreational benefits of these policies using total payroll in specific NAICS industries for counties in the Sacramento Valley watershed. From these results it is clear the costs, and in particular the spillovers to fossil fuel generation, of these minimum flow policies are of similar magnitude compared to the *total* economic activity from recreation activities. Only the broad Food and Drinking Establishments and Total Recreation categories report annual payroll in excess of the estimated costs of these policies.[43]

The magnitude of electricity market costs are also large compared to the total value consumers may place on river-related recreation in the Sacramento Valley. The California State Park System reports total annual visitors to state parks in regions adjoining the Sacramento Valley River system[44] range from six to seven million visitor-days per year, implying policy-related electricity market costs of two to twenty three dollars per visitor day. The US Bureau of Reclamation reports use-related valuations of river activity ranging from $13.67 to $34.75 per visitor-day in 2015 dollars.[45] The local average treatment effect (LATE) of instream flow policies on electricity market costs comprise somewhere between 8% to 146% of the *total* value of recreation activity in the Sacramento Valley.

6.7 Potential channels for spillovers

There are a number of potential channels through which restrictions on the behavior of hydroelectric generators may lead to inefficiencies which spill over into fossil fuel generation. First, policies imposing increased (more stringent) minimum discharges will reduce the elasticity of supply of hydroelectric generation, forcing fossil fuel generators to absorb more of the variability in residual demand. Fossil fuel generators face non-trivial adjustment costs and increased variability will lead to reduced efficiency. These effects would manifest at the plant-level as an increase in load variability or an increase in the likelihood a plant is called on to start generating electricity after being idle.

Second, as described in Section 3.3, there is substantial evidence increased water scarcity pushes the generation mix to fossil fuel generating units with lower cooling water requirements. In general, these units are less efficient at converting heat into electricity. Thus, the effect of water scarcity would manifest through decreased reliance on water-intense plants or plants using fresh water for cooling. While these minimum flow policies considered here do not directly affect the total quantity of surface water available, they alter decisions on the timing and rate at which water is discharged through the river system and may simulate increased water scarcity as dams are forced to meet more stringent minimum flow requirements.

I investigate the role of each potential mechanism for each of the policy changes by applying the RDD described in Section 5.1 to additional outcome variables related to each of these mechanisms. The

[43] It is reasonable both the Food and Drinking Establishments and Total Recreation categories would not respond substantially to changes in the minimum flow policies. The Sacramento Valley contains the Sacramento MSA with an urban population over 1.7 million as of 2010. There are also a number of casinos in the Sacramento valley which are included in the Recreation category. Neither of these industries are likely to be substantially affected by changes in river flow.

[44] I consider parks in the Central Valley, Gold Fields, Northern Butts, and Sierra Park Districts.

[45] Range of valuations from Platt (2001) deflated to 2015 dollars from the date of each study using the CPI for all goods.

estimates for the narrowest feasible bandwidth are shown in Table 10.

Rows one through three investigate the load variability channel. Both load variability and the number of startups increase with the BN→AN policy. This is broadly consistent with spillovers to fossil fuel generation being driven by policy-induced reduction in the supply elasticity of hydroelectric generation. The large minimum flow requirements of the BN→AN policy leave little room for dams to adjust output, increasing the levels of load variability that must be absorbed by fossil fuel generation. This is not, however, the case with the CD→D policy. Even though flow requirement for dams increase as a result of this policy, they are generally still far below the maximum output of each dam and allow for substantial adjustment of output to market signals.

This is not the first evidence that load variability increases the costs of fossil fuel generators. Reguant (2014) shows the fixed cost of starting up a thermal generator can be substantial and Cullen (2013) finds increases in the variability of electricity supplied by wind power moderately decreases the thermal efficiency of electricity generators. Likewise, Bushnell and Novan (2021) find increasing solar deployments reduce daytime prices but increase prices in the shoulder hours when the sun is rising or setting. While my results implicate load variability as a driver of the reduction in thermal efficiency, the estimated costs represent the entirety of the policy, not just the component of cost attributable to increased variability in residual fossil fuel load.

Turning to the role of water scarcity on spillovers, the CD→D policy leads to reliance on less-water intense plants, measured by the mean rate of water intake per MW of power generated (row four) and plants that use cooling systems that do not use fresh water (row five).[46] Less-water intense generation generally comes at a cost to efficiency, which is borne out in the data. The design heat rate of the mean plant under under the CD→D policy is 0.7 mmBTU/MWh, or about 7% to 10% less efficient. Each of these results are consistent with increased minimum flow requirements under the CD→D policy leaving less water available for other applications, such as power plant cooling. Conversely, under the BN→AN policy, scarcity of cooling water is likely not a limiting factor in fossil fuel operations and the policy has no statistically significant effect on the mix of cooling systems used in fossil fuel generation.

Estimates for the D→BN policy show that perhaps both mechanisms contribute to spillovers under this policy. Load variance and the number of starts appear to increase as a result of increased stringency in flow restrictions, but the policy also leads to less reliance on water-intensive fossil fuel generation. In many cases the magnitude of these effects are larger than under the other policies, however, the overall effect on fossil fuel generation efficiency from Table 6 is similar to the effect of other flow policies.

7 Implications

Any binding regulation, by the simple fact that it constrains firms from taking actions which would maximize profits, will reduce profitability of the regulated firms. Other firms not bound by the regulation but connected through input or output markets may respond in privately optimal ways which also reduce their

[46] I consider plants reporting their cooling systems as drawing either fresh surface water or ground water as using fresh water for cooling. Alternatively, plants may use dry cooling systems or rely on seawater or treated wastewater for cooling.

efficiency compared to an unregulated market. Any evaluation of the costs of regulation should account for both the direct costs and spillovers to unregulated firms.

Here, I consider a suite of regulations governing the allowed rate of discharges from hydroelectric dams and their impact on the total cost of producing electricity from both hydroelectric and fossil fuel sources. Empirical estimates show the direct effect of more stringent regulations is substantial, reducing the value of electricity produced by hydroelectric dams by more than 6%. More importantly, these regulations impact the decisions of fossil fuel generators selling electricity in the same market. Misallocation of hydroelectric supply over time increases total system costs as much as 10%, as high-cost producers are called on more often during periods of high demand. Further, there is a productive inefficiency as individual plants consume additional fuel to produce similar levels of output, increasing costs as much as 16% per unit of electricity generated. Due to the sheer size of the fossil fuel generating sector, spillover costs account for more than half of the total costs of the policy. This underscores the conclusion that analyses of regulation should consider both the direct and spillover costs when determining the optimal level of regulation.

Unlike other analyses of regulation or regulatory spillovers, there are multiple transitions between the five distinct levels of regulatory stringency in this setting. The allows comparison of spillover effects under a range of policy options. As policy stringency increases, the magnitude of the productive inefficiency at fossil fuel plants increases along with direct effect of the policy on hydroelectric dams. The allocative inefficiency, however, does not follow the direct effect. Allocative inefficiencies are near zero in years with moderately abundant water – where dams have large discretionary water reserves and the electricity supply the most elastic. This coincides precisely with theoretical predictions; allocative effects are the largest when supply is inelastic. From this we can draw two important conclusions. Spillover effects can be large, but depend critically on the elasticity of supply and demand under regulation, which requires analysis of each specific regulation and market. Second, when designing regulation, policies promoting markets with higher supply and/or demand elasticity will face smaller costs from the allocative effect.

In this specific context there are additional margins for reducing the spillover costs. In many cases – particularly with peaking flows – dam operators could be given the discretion to defer discharges to periods where the electricity generated would have higher social value, while still achieving the environmental objectives of the instream flow policies. The instream flow requirements, however, are rigid and written into the FERC operating licenses for each hydroelectric dam, preventing even efficiency-improving reallocation of discharges. Kosnik (2014) demonstrates increasing flexibility in some terms of FERC licenses as they are renewed over time. Allowing increased flexibility in how dams meet their schedule of required instream flows has the potential to lead to substantial reductions in electricity generation costs, with negligible environmental impact.

One should also consider how the magnitude of these spillovers may evolve over time. As described in Section 6.7, the primary driver of spillovers from the CD→D policy into fossil fuel generation is increased water scarcity shifting the generating mix toward less water-intense generating units. Looking to the future, Medellín-Azuara et al. (2007) find agricultural and urban demands for water in California are expected to grow by 5% by 2050, reducing water available for other uses. On the supply side, continuing climate change can have a profound impact on water scarcity. Null and Viers (2013) develop models predicting the future distribution of total unimpaired runoff and the resulting WYT classification in the Sacramento Valley under a range of climate models. Through 2050 these models predict anything from a small increase in years with an AN or W type to sharp increase in CD and D WYTs. Any increases in water scarcity will only exacerbate the costs computed here.

The primary driver of costs under the BN→AN policy, however, is the variability in residual demand faced by fossil fuel generators. California's Senate Bill 350 has set the ambitious goal of requiring 50% of all electricity consumed in California to be derived from renewable sources. As the portion of renewable generation increases, the variance in hour-to-hour residual demand will increase as well. Constraints on the ability of hydroelectric generation to absorb variability forces fossil fuel generators – with large adjustment costs – to more often alter output in response to changing demand.

This relationship is demonstrated in Figure 9, which shows mean hourly generation by large hydroelectric dams and non-dispatchable renewables for weekdays in April of 2014, 2015, and 2016. Renewable generation – particularly solar PV which provides peak power around noon – increased substantially throughout this time frame. As solar generation has expanded, average hydroelectric generation has increased in periods when load net of renewables is rapidly changing. While the levels are dependent on the quantity of water available for discharge, it is clear the within-day variance in hydroelectric generation is becoming larger, in fact Auffhammer, Baylis, and Hausman (2017) note peak loads will increase much more than average over the next century. Constraints on the adjustability of hydroelectric generation will require fossil fuel generators to absorb more of the variability in demand and increase the level of spillovers from minimum flow policies. This highlights the importance of flexibility in hydroelectric output, not only in California, but any region transitioning electricity generation to a large stock of intermittent generation.

Finally, the results I present in this paper consider the cost of supplying electricity while holding the capital stock fixed. Recent research, including Boomhower and Davis (2020), has noted some energy efficiency investments can result in substantial capital cost savings by reducing demand for reserve electricity generation capacity. Hydroelectric generation can provide similar benefits on the supply side by allocating its generation to the hours of highest demand, reducing the need for costly and infrequently-used reserve thermal generation capacity. While I am unable to directly estimate the impact of instream flow policies on reserve capacity requirements, any policy restricting the ability of hydroelectric dams to generate at capacity in the periods of highest demand would increase total system capital costs.

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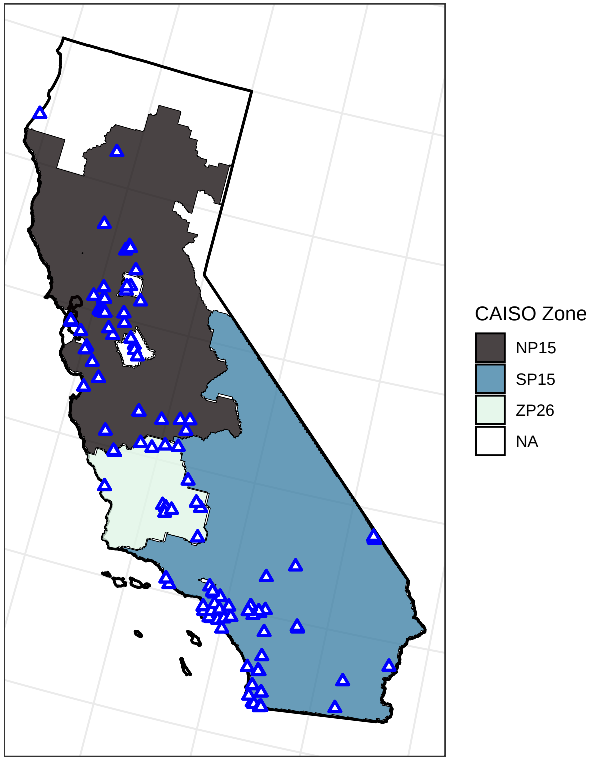
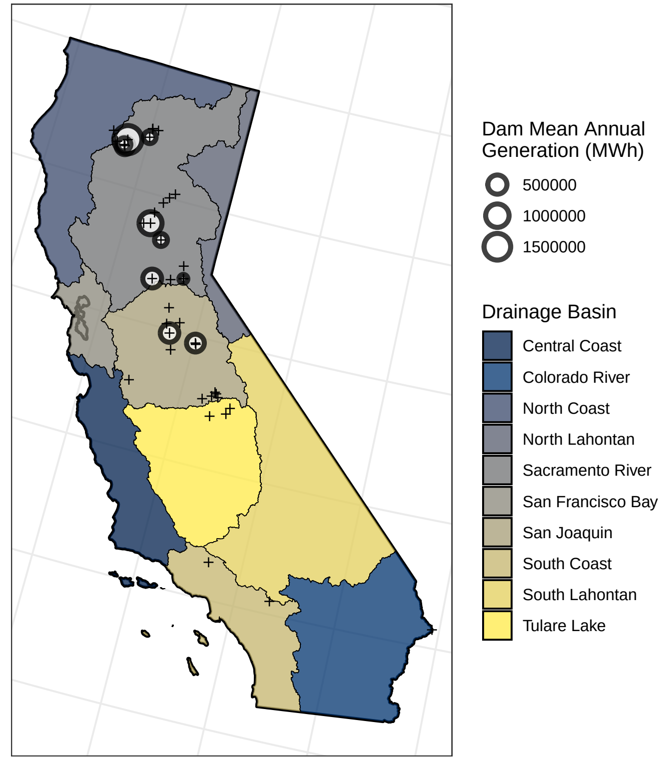
Figure 1: Map of California Electricity Generating Regions, Drainage Basins, and Electricity Generating Plants

(a) Fossil fuel generators and electricity generating regions



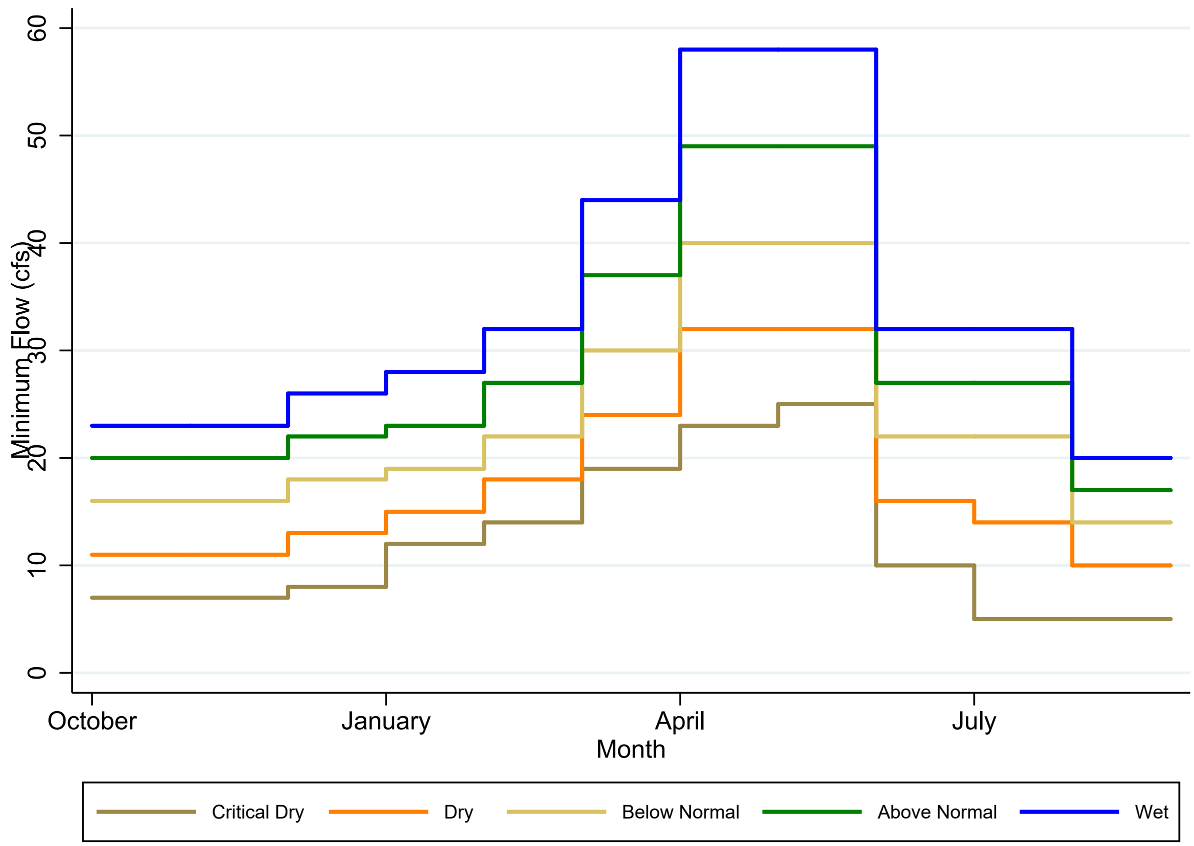
Map of California fossil fuel generating units (marked with a triangle) and electricity generating regions. The electricity generators considered here are in the NP15 region in the North.

(b) Hydroelectric generators and drainage basins



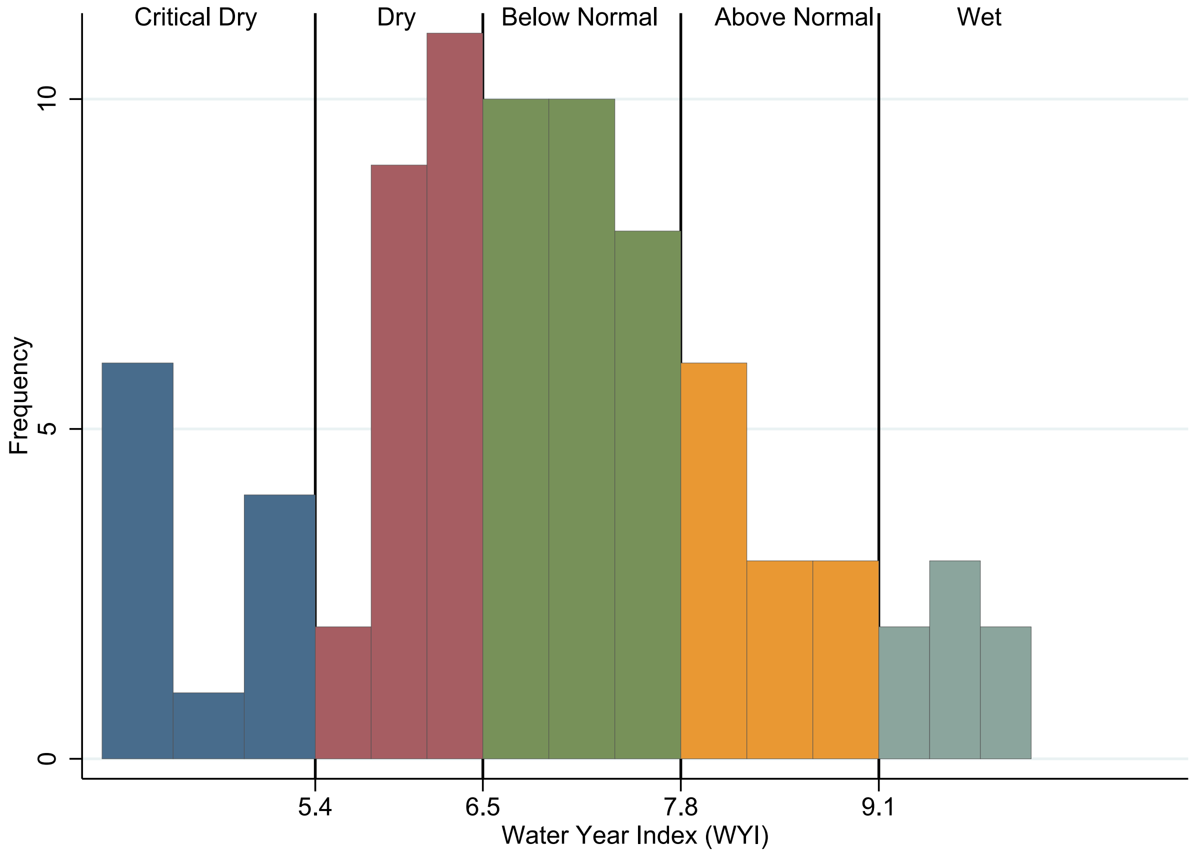
Map of large ($\geq$ 100 MW nameplate capacity) hydroelectric dams and CADWR drainage basins. Each dam is marked with a + overlaid on a circle which increases in diameter linearly with annual generation of the dam. The dams considered here are in the Sacramento Valley drainage basin of the central North, which represent the bulk of hydroelectric generation in California.

Figure 2: Minimum flow on Gerle Creek below Loon Lake Reservoir by WYT



Required minimum flows on Gerle Creek south of Look Lake Reservoir Dam by WYT and month. For the months of February, March, April, and May regulations take effect three days after the monthly Bulletin 120 forecast is issued and are binding until two days after the release of the next forecast.

Figure 3: Histogram of water year indices, 1990 to 2016

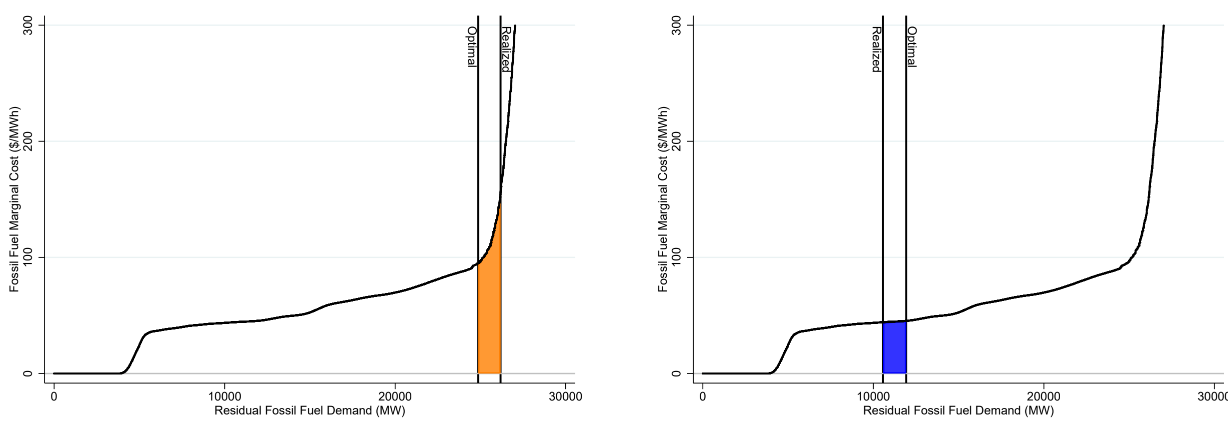


Histogram of WYI for the Sacramento Valley reconstructed from each Bulletin 120 forecast from the California Department of Water Resources. Forecasts are released on the first Monday of each February, March, April, and May. Thresholds for each WYT are vertical black lines.

Figure 4: Example change in fossil fuel generation costs from hydroelectric reallocation

(a) Reallocation on July 6th, 2007 at 00:00 UTC

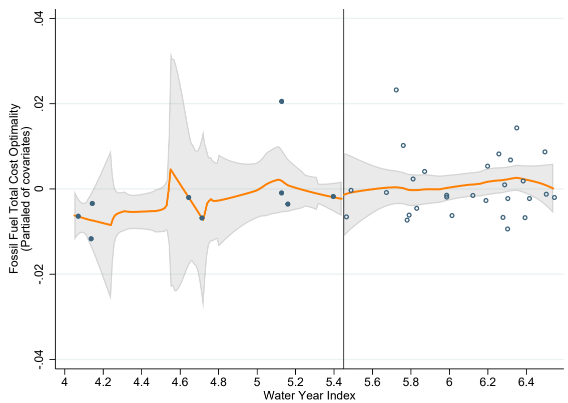
(b) Reallocation on July 1st, 2007 at 00:00 UTC



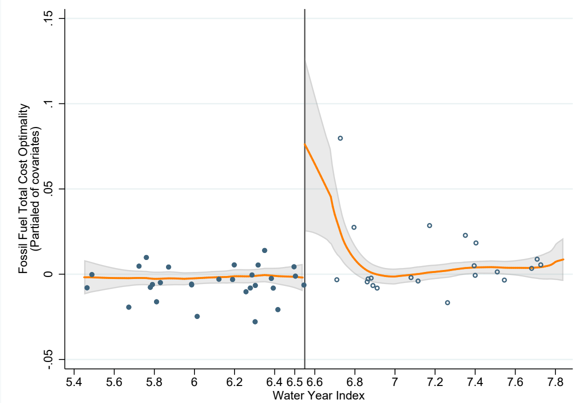
The graph illustrates computing the change in total fossil fuel generating costs resulting in a reallocation of hydroelectric generation at the specified time. The upward-sloping curve is the marginal cost of fossil fuel generation over the range of potential levels of residual fossil fuel demand, computed using methods similar to Borenstein, Bushnell, and Wolak (2002). The right vertical line is the observed residual fossil fuel demand. The left vertical line is counterfactual residual fossil fuel demand where hydroelectric output is reallocated over time to minimize total fossil fuel generation costs. The shaded area between observed and counterfactual demand and under the marginal cost curve represents the change in total fossil fuel generation costs resulting reallocations in this hour. Panel (a) represents a reallocation which increases hydroelectric generation and decreases marginal cost in that hour. Panel (b) decreases hydroelectric generation and increases marginal cost.

Figure 5: Regression discontinuity total generation cost optimality

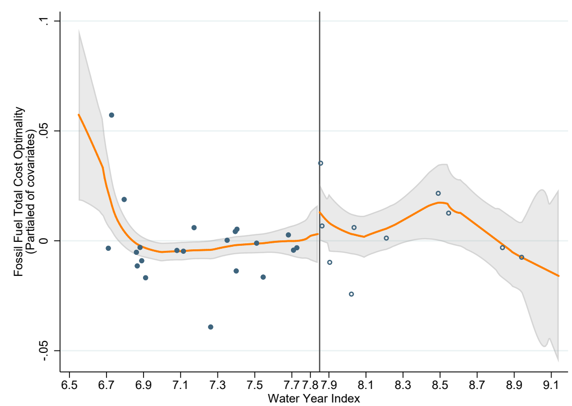
(a) Policy threshold CD→D



(b) Policy threshold D→BN



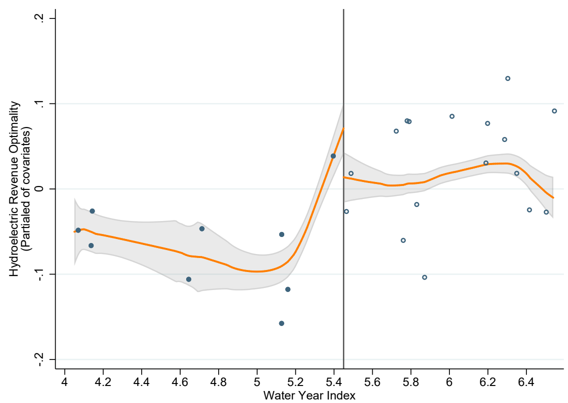
(c) Policy threshold BN→AN



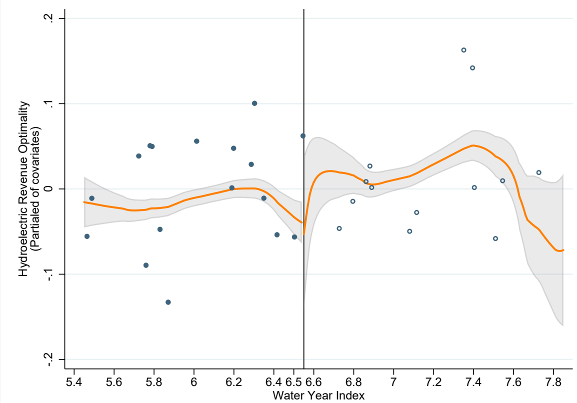
Binned scatter plot of the ratio of excess electricity generation costs relative to perfect cost-minimization as a function of WYI. Bins constructed with approximately 15 observations on each side of the threshold. Lowess trends with 95% confidence intervals for each side of the discontinuity shown as the shaded region and line. Policy discontinuity shown as the vertical line.

Figure 6: Regression discontinuity hydroelectric generation revenues

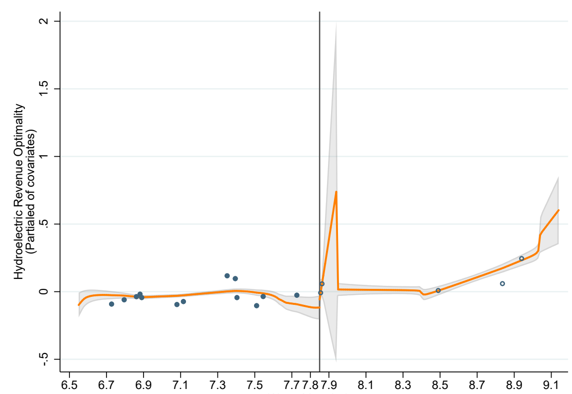
(a) Policy threshold CD→D



(b) Policy threshold D→BN



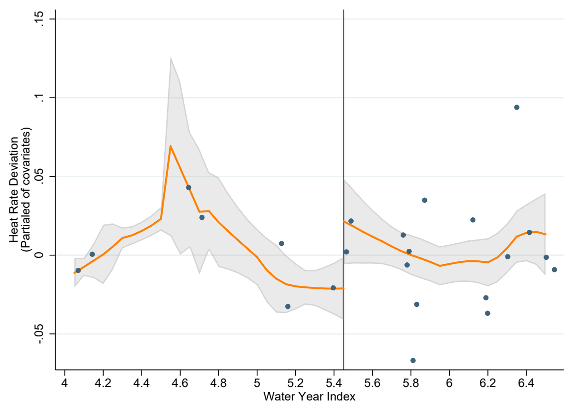
(c) Policy threshold BN→AN



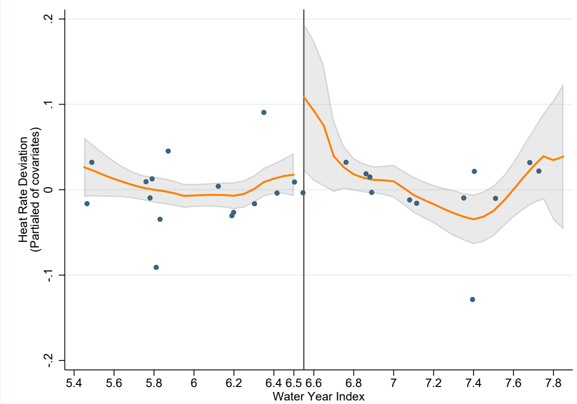
Scatter plot of the ratio of realized hydroelectric generation revenues relative to *ex post* profit maximization as a function of WYI. Scatter observations collapsed to approximately 15 observations on each side of the threshold. Lowess trends with 95% confidence intervals for each side of the discontinuity shown as the shaded region and line. Policy discontinuity shown as the vertical line.

Figure 7: Regression discontinuity plot of heat rate devisions

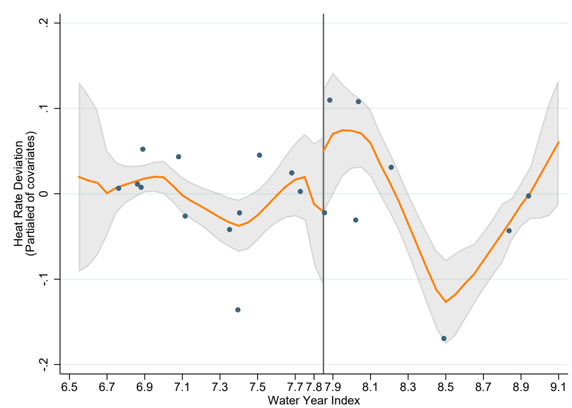
(a) Policy threshold CD→D



(b) Policy threshold D→BN



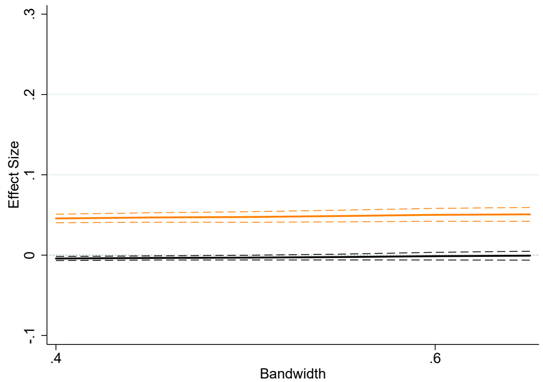
(c) Policy threshold BN→AN



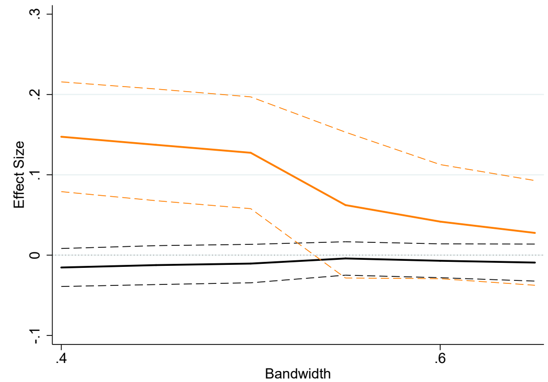
Binned scatter plot of quantity-weighted deviations from average plant heat rates as a function of WYI. Bins constructed to produce approximately 15 observations on each side of the threshold. Lowess trends with 95% confidence intervals for each side of the discontinuity shown as the shaded region and line. Policy discontinuity shown as the vertical line.

Figure 8: Placebo treatment: Untreated outcomes

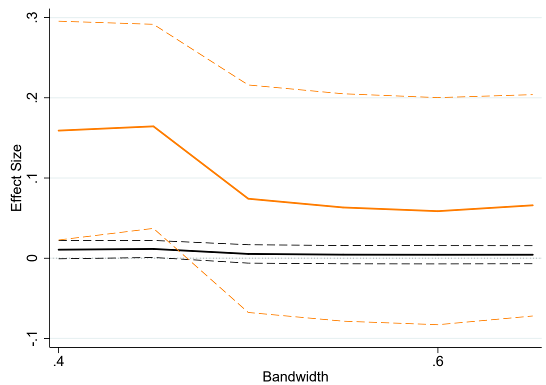
(a) Policy Threshold CD→D



(b) Policy Threshold D→BN

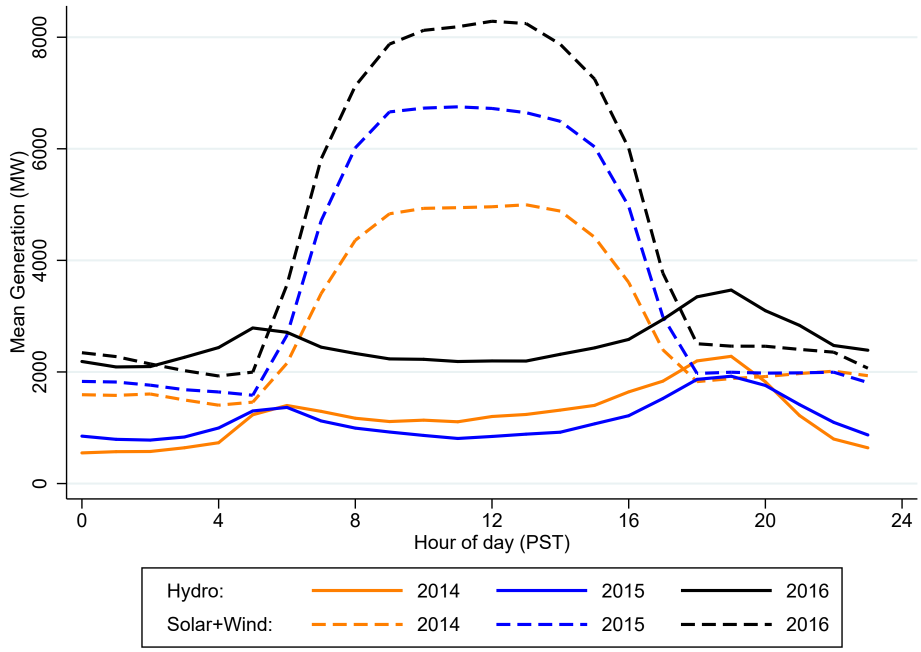


(c) Policy Threshold BN→AN



Estimates of policy treatment effects on natural gas generator heat rates for the primary sample (orange) and a placebo sample (black) across a range of RDD bandwidths. The placebo sample consists of natural gas-fired power plants in the ERCOT region of Teaxs during the same period and using the same running variable and policy thresholds as the primary specification. Pointwise 95% confidence intervals shown as dashed lines.

Figure 9: Mean Hydroelectric and Other Nondispatchable Generation by Hour



Mean hourly electricity generation in CAISO by large hydroelectric dams (solid) and non-dispatchable renewables (dashed, wind and solar PV) for weekdays in April of the specified year.

Table 1: Example water year type determination

Sacramento Valley Water Year Hydrologic Classifications are:

Year Type	Water Year Index
Wet	Equal to or greater than 9.2
Above Normal	Greater than 7.8, and less than 9.2
Below Normal	Greater than 6.5, and equal to or less than 7.8
Dry	Greater than 5.4, and equal to or less than 6.5
Critical	Equal to or less than 5.4

Source: California Department of Water Resources, 2009, *CA Water Plan Update 2009*, Vol. 4 Reference Guide. The WYI is computed as a weighted average of past and forecast future stream flows through the Sacramento River system as described in Equation 2. Since 1990, values have ranged from 3.1 to 14.9.

Table 2: Example minimum streamflow regulations

Gerle Creek below Loon Lake Reservoir Dam					
Minimum Streamflow by Water Year Type (cfs)					
Month	**CD**	**DRY**	**BN**	**AN**	**WET**
October	7	11	16	20	23
November	7	11	16	20	23
December	8	13	18	22	26
January	12	15	19	23	28
February	14	18	22	27	32
March	19	24	30	37	44
April	23	32	40	49	58
May	25	32	40	49	58
June	10	16	22	27	32
July	5	14	22	27	32
August	5	10	14	17	20
September	5	10	14	17	20

Source: Upper American River Hydroelectric Project Minimum Flows. Minimum instream flows below Loon Lake Reservoir Dam as specified in the dam's operation license from FERC.

Table 3: Comparison of official and reconstructed WYI and WYT

		Reconstructed		Official	
Year	Month	WYI	WYT	WYI	WYT
1995	May	12.397	W	12.4	W
1996	May	9.708	W	9.7	W
1997	May	11.005	W	11.0	W
1998	May	12.361	W	12.4	W
1999	May	10.044	W	10.0	W
2000	May	9.229	W	9.2	W
2001	May	5.871	D	5.9	D
2002	May	6.503	D	6.5	D
2003	May	8.036	AN	8.0	AN
2004	May	7.681	BN	7.7	BN
2005	May	7.395	BN	7.4	BN
2006	May	13.023	W	13.0	W
2007	May	6.199	D	6.2	D
2008	May	5.396	C	5.4	C
2009	May	5.489	D	5.5	D
2010	May	6.881	BN	6.9	BN
2011	May	10.022	W	10.0	W
2012	May	6.861	BN	6.9	BN
2013	May	5.790	D	5.8	D
2014	May	4.019	C	4.0	C
2015	May	3.965	C	4.0	C
2016	May	7.115	BN	7.1	BN
2017	May	14.903	W	14.9	W
2018	May	7.163	BN	7.2	BN
2019	May	10.210	W	10.2	W

Comparison of the measure of WYI and WYT designations reconstructed from CADWR Bulletin 120 and official values of the WYI and WYT reported by the CADWR. Archival official values are only available for May forecasts from 1995 to the present. CADWR rounds the WYI to the nearest 0.1 when reporting the WYI and determining the WYT.

Table 4: Effect of minimum flow policies on total fossil fuel generation costs

(a) Policy threshold CD→D

Bandwidth	0.40	0.45	0.50	0.55	0.60	0.65
LATE	0.001	0.001	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Obs. Left	11	11	11	11	11	11
Obs. Right	26	31	31	33	34	34

(b) Policy threshold D→BN

Bandwidth	0.40	0.45	0.50	0.55	0.60	0.65
LATE	0.104	0.100	0.098	0.078	0.048	0.036
	(0.051)**	(0.052)*	(0.052)*	(0.046)*	(0.033)	(0.027)
Obs. Left	29	30	30	31	33	33
Obs. Right	19	19	19	23	28	29

(c) Policy threshold BN→AN

Bandwidth	0.40	0.45	0.50	0.55	0.60	0.65
LATE	0.008	0.008	0.018	0.019	0.019	0.017
	(0.011)	(0.010)	(0.010)*	(0.010)*	(0.010)*	(0.010)*
Obs. Left	12	14	20	20	21	21
Obs. Right	13	13	13	13	13	17

Each panel shows the change in the ratio of excess electricity generation costs relative to perfect cost-minimization resulting from the specified policy change estimated using the RDD described in Section 5.1 conditional on month-of-year fixed effects. Each observation is a 28-day period starting on the second Monday of the month. Standard errors clustered by the CADWR WYI designation period, updated in February, March, April, May, and October, are shown in parentheses. *,**,*** denote results significant at the 10%, 5%, and 1% levels, respectively.

Table 5: Effect of minimum flow policies on hydroelectric generation value

(a) Policy threshold CD→D

Bandwidth	0.40	0.45	0.50	0.55	0.60	0.65
LATE	-0.066	-0.062	-0.059	-0.057	-0.058	-0.059
	(0.033)**	(0.033)*	(0.033)*	(0.033)*	(0.033)*	(0.033)*
Obs. Left	146	146	146	146	146	146
Obs. Right	332	392	392	417	429	429

(b) Policy threshold D→BN

Bandwidth	0.40	0.45	0.50	0.55	0.60	0.65
LATE	-0.072	-0.069	-0.068	-0.012	0.048	0.065
	(0.030)**	(0.030)**	(0.030)**	(0.050)	(0.056)	(0.054)
Obs. Left	359	367	367	379	404	404
Obs. Right	223	223	223	274	315	315

(c) Policy threshold BN→AN

Bandwidth	0.45	0.50	0.55	0.60	0.65
LATE	-0.071	0.026	0.059	0.074	0.153
	(0.033)**	(0.054)	(0.073)	(0.081)	(0.087)*
Obs. Left	98	183	183	192	192
Obs. Right	21	21	21	21	76

Each panel shows the change in ratio of realized hydroelectric generation revenues relative to *ex post* profit maximization resulting from the specified policy change. Standard errors two-way clustered at the forecast month and plant level shown in parentheses. *,**,*** denote results significant at the 10%, 5%, and 1% levels, respectively.

Table 6: Effect of instream flow requirements on plant-level heat rate deviations

(a) Policy threshold CD→D

Bandwidth	0.40	0.45	0.50	0.55	0.60	0.65
LATE	0.046	0.047	0.047	0.049	0.050	0.051
	(0.003)***	(0.003)***	(0.003)***	(0.004)***	(0.004)***	(0.004)***
Obs. Left	11	11	11	11	11	11
Obs. Right	26	31	31	33	34	34

(b) Policy threshold D→BN

Bandwidth	0.40	0.45	0.50	0.55	0.60	0.65
LATE	0.147	0.137	0.127	0.062	0.042	0.028
	(0.035)***	(0.035)***	(0.035)***	(0.046)	(0.036)	(0.033)
Obs. Left	29	30	30	31	33	33
Obs. Right	18	18	19	23	26	27

(c) Policy threshold BN→AN

Bandwidth	0.40	0.45	0.50	0.55	0.60	0.65
LATE	0.159	0.164	0.074	0.063	0.059	0.066
	(0.070)**	(0.065)**	(0.072)	(0.072)	(0.072)	(0.070)
Obs. Left	12	14	20	20	21	21
Obs. Right	13	13	13	13	13	17

Each panel shows the quantity-weighted deviations from average plant heat rates from the specified policy change estimated using the RDD described in Section 5.1 conditional on month-of-year fixed effects. Each observation is a 28-day period starting on the second Monday of the month. Standard errors clustered by the CADWR WYI designation period, updated in February, March, April, May, and October, are shown in parentheses. *,**,*** denote results significant at the 10%, 5%, and 1% levels, respectively.

Table 7: Social cost of minimum flow policies in electricity generation

Instream Flow Policy	Mean Annual FF Cost ($M/yr)	Allocative Inefficiencies ($M/yr)	Productive Inefficiencies ($M/yr)	CO_2 Externality ($M/yr)	Local Criteria Externality ($M/yr)	Total Social Cost ($M/yr)
CD→D	365.20	0.46	13.86	4.14	0.25	18.72
D→BN	504.69	47.37	52.58	23.85	2.65	126.46
BN→AN	382.95	2.98	42.04	12.83	1.99	59.85

Estimated costs related to electricity generation of transitioning between minimum flow policies for the specified WYT designations in $M/year. Fossil fuel generation costs computed using WYT-specific averages from 2006 to 2016, 2015 fuel prices, and reported in 2015 dollars using the CPI, all items, seasonally adjusted. Allocative inefficiencies are direct costs resulting from the misallocation of hydroelectric generation over time, described in Section 6.1. Productive inefficiencies are spillovers from instream flow policies to fossil fuel generators, described in Section 6.3. Value of CO_2 additional damages is the 2015 social cost of carbon of $38/ton from IAWG (2013). Local criteria pollutant damages for nitrogen oxides (NO_X) and sulfur dioxide (SO_2) computed using county-specific marginal damages estimates from Muller (2014). Effects estimated using the smallest feasible bandwidth from RDD estimators.

Table 8: Other costs of instream flow policies

Policy Name	Base Outflows	Policy-Induced Outflows	Environmental Costs ($M/yr)	Agricultural Costs ($M/yr)	Total Costs ($M/yr)
CD→D	199	153	9.98	38.83	48.81
D→BN	364	276	42.44	68.19	110.63
BN→AN	1,833	215	140.02	159.40	299.42

Estimated benefits of instream flow policies derived from the CALVIN model. Benefits expressed in millions of dollars per year using 2015 dollars. Policy-Induced outflow represent the increase in annual Delta outflows in Maf. Costs are the total cost per year of the specified policy change. Environmental costs represent forgone use of water for other environmental policy goals. Agricultural costs represent lost agricultural productivity due to forgone water use.

Table 9: Economic activity by NAICS code

NAICS Code	NAICS Description	Mean Number of Establishments	Imputed Annual Payroll ($M)
114—	Fishing, Hunting, Traping	10.8	1.9
532292	Water ski/personal watercraft renting	45.6	12.1
7121–	Musems, historical sites, etc.	69.2	17.1
712190	Natural wonder tourist attractions	14.6	3.5
7139–	Recreation (incl. casinos)	722.5	262.4
713990	Other Amusement/Recreation	169.1	17.1
72121-	RV Parks and campgrounds	129.8	23.1
722—	Food and Drinking Establishments	6,111.8	1,537.3

Mean annual payroll for establishments benefiting from environmental and recreation constraints on dam discharges for counties in the Sacramento Valley. Imputed using observed number of establishments and mean payroll per establishment from County Business Patterns data from 1998 to the present. Dollar value deflated to 2015 using the annual average CPI all goods.

Table 10: Decomposition of spillover channels

Policy	CD→D	D→BN	BN→AN
WYI Threshold	5.4	6.5	7.8
Variance in Load	-0.01445	0.01370	0.00742
Portion of Capacity	(0.00073)***	(0.00731)*	(0.00298)**
Startups	-0.00440	0.00287	0.00119
Per plant-hour	(0.00005)***	(0.00047)***	(0.00052)**
Cold Startups	-0.00423	0.00123	0.00106
Per plant-hour	(0.00008)***	(0.00055)**	(0.00043)**
Cooling Water Intensity	-11,261	-124,312	62,030
gal/min/MW	(2,349)***	(5,260)***	(59,034)
Use fresh water for cooling	-0.1128	-0.1552	0.1170
Portion of Load	(0.0057)***	(0.0048)***	(0.0664)*
Typical Heat Rate	0.70	2.72	-0.72
mmBTU/MWh	(0.32)**	(0.05)***	(0.20)***

Standard errors two-way clustered by month and plant shown in parentheses. *,**,*** denote coefficients significant at the 10%,5%, and 1% levels, respectively. Variance in load is the plant-level variance in the plant load rate (load/max load). Startups is the hourly plant-level probability of transitioning from zero output to some non-zero level of output. Cold Startups is the hourly plant-level probability of transitioning to a non-zero level of output after at least four hours of zero output. Typical heat rate is the current-year mean heat rate of the plant *excluding* the current month. Cooling water intensity is the plant-level mean intake rate of water for cooling. Use fresh water for cooling is the grid-level probability dispatched plants use fresh water (as opposed to dry systems, seawater, or treated wastewater) for cooling.