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

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Appendices
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A Theory

A.1 Additional details of the two period model

This section provides additional detail for and results from the two-period model of the electricity section presented in Section 2 of the paper.

A.1.1 Assumptions underlying model results

In deriving necessary conditions for the two-period model of the electricity sector, I will make the following simplifying assumptions:

- *Demand in each period is exogenous, perfectly inelastic, and varies ($Q_0 \neq Q_1$).* This assumption guarantees there exists a level of the minimum generation requirement $\underline{Q}^H$ such that the constraint binds in one period and not in the other.
- *Non-negativity constraints never bind on fossil fuel generation.* This assumption rules out realizations of exogeneous model parameters where the reserve constraint does not bind.
- *The discount factor is one.* This assumption is for notational simplicity. In the case where $\beta < 1$ the social planner will set the present value of marginal costs equal across all periods, but the qualitative conclusions are the same.

A.1.2 Effect of minimum generation constraints on producer surplus

This model also provides insight to how minimum generation constraints may impact the producer surplus in each sector of the electricity market. As a prelude, I will highlight some results required to analyze surplus. First, in a competitive market, if the quantity of fossil fuel generation is greater than zero the price paid for electricity will be the marginal cost of increasing electricity supply which is simply the marginal cost of fossil fuel generation.

Second, a marginal increase in the minimum hydroelectric generation constraint will increase Q_i^H and decrease Q_j^H by that same margin. (Since the total reservoir constraint binds hydroelectric production, the implicit derivatives of the optimal quantities with respect to the constraint are 1 and -1 respectively.) Since demand is perfectly inelastic, this implies that same marginal increase in the minimum generation constraint will decrease Q_i^F and increase Q_j^F (implicit derivatives are -1 and 1 respectively).

Considering the surplus accruing to the fossil fuel generating sector, the producer surplus is the sum of revenues minus the sum of costs:

$$PS^F = Q_i^F \cdot \frac{\partial TC}{\partial Q^F}\bigg|_{Q_i^F} + Q_j^F \cdot \frac{\partial TC}{\partial Q^F}\bigg|_{Q_j^F} - TC(Q_i^F) - TC(Q_j^F) \tag{1}$$

The marginal change in surplus with respect to a change in the minimum generation constraint is:

$$\frac{\partial PS^F}{\partial \underline{Q}^H} = Q_i^F \cdot \frac{\partial^2 TC}{\partial (Q^F)^2}\bigg|_{Q_i^F} - Q_j^F \cdot \frac{\partial^2 TC}{\partial (Q^F)^2}\bigg|_{Q_j^F} \tag{2}$$

Since fossil fuel generators behave competitively, the second derivative of the total cost function is the derivative of the fossil fuel supply function. I can express the marginal change in fossil fuel producer surplus as a function of the fossil fuel supply elasticities (ε_t^F) in each period:

$$\frac{\partial PS^F}{\partial \underline{Q}^H} = \varepsilon_i^F - \varepsilon_j^F \tag{3}$$

This is a straightforward and intuitive result. In the face of an increase in the strigency of a minimum hydroelectric generation constraint, producer surplus will increase for fossil fuel generators when supply is more elastic in period i, where the minimum generation policy binds, than in period j. In that case, the increase in hydroelectric generation in period i (and corresponding decrease in fossil fuel generation) has a smaller effect on prices than the required increase in fossil fuel generation in period j.

It is also useful to consider how a change in the minimum generation constraint may impact the surplus earned by hydroelectric generators. Hydroelectric generation has zero marginal cost, thus the producer surplus of the hydroelectric sector is:

$$PS^H = Q_i^H \cdot \frac{\partial TC}{\partial Q^F}\bigg|_{Q_i^F} + Q_j^H \cdot \frac{\partial TC}{\partial Q^F}\bigg|_{Q_j^F} \tag{4}$$

This leads to marginal surplus with respect to a change in the binding minimum generation constraint:

$$\frac{\partial PS^H}{\partial \underline{Q}^H} = \underbrace{\frac{\partial TC}{\partial Q^F}\bigg|_{Q_j^F} - \frac{\partial TC}{\partial Q^F}\bigg|_{Q_i^F}}_{\text{Marginal Effect}} \underbrace{+ Q_j^H \cdot \frac{\partial^2 TC}{\partial (Q^F)^2}\bigg|_{Q_j^F} - Q_i^H \cdot \frac{\partial^2 TC}{\partial (Q^F)^2}\bigg|_{Q_i^F}}_{\text{Inframarginal Effect}} \tag{5}$$

The term in the first set of brackets is the marginal effect on revenues from reallocating a unit of water from a period of high prices to a period of lower prices due to the minimum generation requirement. This difference is always negative.

The second term is the change in inframarginal revenues. Reallocating water decreases prices (and revenues for all inframarginal units) in the period where hydroelectric generation is bound by the constraint (i) and increases prices in the other period (j). In each period, the change in inframarginal revenues is the inframarginal quantity times that change in price.

The sign of this effect depends on the convexity of the fossil fuel cost function and the allocation of inframarginal generation. For example, if the second derivative of the cost function is increasing then prices increase more in period j than they fall in period i from a marginal change in the minimum hydroelectric generation constraint. If the inframarginal quantity of hydroelectric generation in period j is sufficiently large compared to period i then total revenues will increase as well.[1] Whether the net change in revenues is positive or negative in this case depends on both the third-order behavior of the cost function, the allocation of hydroelectric generation between periods i and j, and the direct effect on prices.

A.2 Infinite Horizon Model of the Electricity Market

The two period model of the electricity sector provides a strightforward model of the channels through which regulations on the output of hydroelectric generators will spill over to fossil fuel generators. In reality, hydroelectric dams optimize the discharge of water in their reservoir over longer time horizons. Here I present a fully dynamic

[1] In this case the minimum generation constraint is forcing the hydroelectric generators to behave like a third-degree price-discriminating monopolist, withholding quantity from a market where demand is inelastic.

discrete-time model of the electricity generation sector. Using this model, I am able to derive necessary conditions for present-value cost minimization that have the same economic interpretation as the simpler two-period model. The setup of the model is quite similar to the two-period model, and I use identical terminology where appropriate.

A.2.1 Electricity Supply

The market for the production of electricity occurs over discrete time periods $t \in \{0, 1, 2, \dots\}$. Electricity can be generated from one of two sources: fossil fuel generators (F) and hydroelectric generators (H). Electricity from either source are perfect substitutes in the output market.

In each period t, fossil fuel generators can generate non-negative quantity of electricity $Q_t^F \geq 0$. The fossil fuel sector has non-negative, increasing, strictly convex cost functions ($TC^F(Q_t^F)$) which are identical in each period.

Changing the output of fossil fuel generation across periods is costly. In each period t, the fossil fuel sector faces adjustment costs $AC(Q_{t-1}^F, Q_t^F)$. Adjustment costs are continuous, twice differentiable, strictly convex and minimized at zero whenever fossil fuel output output is constant across periods ($AC(q,q) = 0\ \forall q$) ($AC(q,s) > 0$ $\forall q \neq s$). These facts imply the following other properties of the adjustment cost function:

Lemma 1. *For all q in the support of Q_{t-1}^F and s in the support of Q_t^F, the following are true:*

1. $\frac{\partial AC}{\partial Q_t^F}\Big|_{q,s} > 0$ *if* $q < s$
2. $\frac{\partial AC}{\partial Q_t^F}\Big|_{q,s} < 0$ *if* $q > s$
3. $\frac{\partial AC}{\partial Q_{t-1}^F}\Big|_{q,s} < 0$ *if* $q < s$
4. $\frac{\partial AC}{\partial Q_{t-1}^F}\Big|_{q,s} > 0$ *if* $q > s$

Proof. Suppose $q = s$ then by definition $AC(q,s)$ is minimized and equal to zero. Choose some $y > s$. Since $AC(\cdot)$ is convex[2]

$$AC(q,s) - AC(q,y) \geq DAC(q,y) \begin{bmatrix} 0 \\ s-y \end{bmatrix}$$
$$0 > AC(q,s) - AC(q,y) \geq \begin{bmatrix} \frac{\partial AC}{\partial Q_{t-1}^F}\Big|_q & \frac{\partial AC}{\partial Q_t^F}\Big|_s \end{bmatrix} \begin{bmatrix} 0 \\ s-y \end{bmatrix}$$
$$0 > (s-y)\,\frac{\partial AC}{\partial Q_t^F}\Big|_s$$
$$(y-s)\,\frac{\partial AC}{\partial Q_t^F}\Big|_s < 0$$

Thus $\frac{\partial AC}{\partial Q_t^F}$ is strictly greater than zero. Proof of part two follows from choosing $y < s$. Parts 3 and 4 follow from choosing some $x < q$ (Part 3) or $x > q$ (Part 4). □

Hydroelectric generators likewise choose a non-negative quantity of output subject to a capacity constraint $Q_t^H \in [0, \overline{Q}^H]$ in each period t. Hydroelectric generators have zero marginal cost, but face a "reserve constraint" ($Q_t^H \leq R_t$) which evolves over time by the law of motion $R_{t+1} = R_t - Q_t^H + I_t$ where I_t represent reservoir inflows between periods t and $t+1$.

[2] Simon and Blume, Theorem 17.8.

Additionally, a regulator exogenously sets hydroelectric "minimum generation constraints" which must be met in both periods ($Q_t^H \geq \underline{Q}^H \; \forall t$).[3] If $\underline{Q}^H > 0$ the non-negativity constraint on Q_t^H is redundant and can be excluded. In the case that the regulator sets no minimum generation requirement, I will set $\underline{Q}^H = 0$ to serve as the non-negativity constraint on hydroelectric generation.

A.2.2 Electicity Demand

Demand for electricity (Q_t) is exogenous and varies each period. Consistent with the nature of demand in wholesale electricity markets, demand is perfectly inelastic in each period.[4] The social planner chooses the quantity of hydroelectric and fossil fuel generation each period which maximizes welfare, subject to non-negativity constraints, and that total supply equal 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.

A.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. The social planner discounts future payoffs with discount factor β.

In each period, the Social Planner observes state variables $Q_t^D, Q_{t-1}^F, R_t, I_t$ and chooses the value of the control variables Q_t^H and Q_t^F that maximize the value function:

$$V_t[Q_t^H, Q_t^F | Q_t^D, Q_{t-1}^F, R_t, I_t] = -TC(Q_t^F) - AC(Q_{t-1}^F, Q_t^F) + \beta V_{t+1}[Q_{t+1}^H, Q_{t+1}^F | Q_{t+1}^D, Q_t^F, R_{t+1}, I_{t+1}] \tag{6}$$

Subject to the following constraints (and Lagrange multiplier)

$$\begin{aligned} Q_t^F + Q_t^H &= Q_t^D & &(eq) \\ R_{t+1} &= R_t + Q_t^H + I_t & &(eq) \\ Q_t^H &\geq \underline{Q}^H & &(\lambda_t) \\ Q_t^H &\leq \overline{Q}^H & &(\delta_t) \\ Q_t^H &\leq R_t & &(\gamma_t) \\ Q_t^F &\geq 0 & &(\phi_t) \end{aligned} \tag{7}$$

Substituting in equality constraints gives the Social Planner's Lagrangian with a single control variable (Q_t^H):

$$\begin{aligned} \mathscr{L} = &- TC(Q_t^D - Q_t^H) - AC(Q_{t-1}^F - Q_{t-1}^H, Q_t^D - Q_t^H) + \\ &\beta V_{t+1}[Q_{t+1}^H | Q_{t+1}^D, Q_t^D, Q_t^H, I_{t+1}] + \\ &\lambda_t(Q_t^H - \underline{Q}^H) + \delta_t(\overline{Q}^H - Q_t^H) + \gamma_t(R_t - Q_t^H) + \phi_t(Q_t^D - Q_t^H) \end{aligned} \tag{8}$$

There are no externalities in this model and 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.

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

[4] 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).

Assumption 1. *The space of feasible hydroelectric output levels is non-degenerate. Thus,*

1. *Minimum and maximum generation constraints at time t permit more than one choice of Q_t^H.* $\underline{Q}_t^H < \overline{Q}_t^H \ \forall t$
2. *For any time range $[a, b]$ reserves and inflows are sufficient to satisfy the minimum generation constraint.* $\sum_{t=a}^{b} \underline{Q}_t^H \leq R_a + \sum_{t=a}^{b} I_t \ \forall a < b$

Assumption 2. *The optimal level of fossil fuel generation is strictly positive in each period.* $Q_t^F > 0 \ \forall t$

For each period t, the Lagrange multipliers λ_t can be interpreted as the shadow cost of a the minimum hydroelectric generation constraint, γ_t is the shadow cost of the reserve constraint in the current period, δ_t is the shadow cost of the maximum flow constraint on hydroelectric generation, and ϕ_t is the shadow cost of the non-negativity constraint on fossil fuel generation.

The SPP's Lagrangian has the following first order condition necessary for cost minimization:

$$\frac{\partial V_t}{\partial Q_t^H} = \frac{\partial TC}{\partial Q_t^F} + \frac{\partial AC}{\partial Q_t^F} - \beta \frac{\partial V_{t+1}}{\partial R_{t+1}} + \lambda_t - \delta_t - \gamma_t + \phi_t = 0 \tag{FOC.1}$$

The following envelope conditions must also hold on the cost-minimizing path:

$$\frac{\partial V_t}{\partial R_t} = \beta \frac{\partial V_{t+1}}{\partial R_{t+1}} + \gamma_t \tag{EC.1}$$

Recursively substituting into Condition (EC.1) gives the following expression for the envelope condition on reserves at time t, which I will call Γ_t

$$\frac{\partial V_t}{\partial R_t} = \sum_{\tau=0}^{\infty} \beta^\tau \gamma_{t+\tau} \equiv \Gamma_t \tag{EC.2}$$

This expression shows the net present value of relaxing the hydroelectric reserve constraint, assuming the optimal path of discharges in the future. This is the true shadow value of water in period t since an increase in reserves in period t may not change hydroelectric generation in period t but caries the option of changing generation in the future as well.

Substituting Condition (EC.2) into Condition (FOC.1) gives:

$$\frac{\partial TC}{\partial Q_t^F} + \frac{\partial AC}{\partial Q_t^F} + \phi_t = \Gamma_t - \lambda_t + \delta_t \tag{NC.1}$$

This expression has a clear economic interpretation. In each period t the sum of the marginal cost of fossil fuel generation, marginal adjustment costs, and the shadow cost of the non-negativity constraint on fossil fuel generation must equal the shadow value of water minus the shadow cost of minimum flow constraints plus the shadow costs of maximum flow constraints on hydroelectric generation.

The optimal dynamic behavior is made clear by subtracting Condition(NC.1) evaluated at time t from the same expression evaluated at time $t + 1$ discounted by one period. This gives:

$$\frac{\partial TC}{\partial Q_t^F} + \frac{\partial AC}{\partial Q_t^F} + \phi_t - \beta \left[\frac{\partial TC}{\partial Q_{t+1}^F} + \frac{\partial AC}{\partial Q_{t+1}^F} + \phi_{t+1} \right] = \delta_t - \lambda_t - \beta \left[\delta_{t+1} - \lambda_{t+1} \right] + \gamma_t \tag{NC.2}$$

Suppose non-negativity constraints on fossil fuel generation (Assumption 2), minimum generation constraints on hydroelectric generation, and maximum generation constraints on hydroelectric generation do not bind in either periods t or $t+1$. Further assume the the reserve constraint does not bind in period t. Then Condition (NC.2) implies

$$\frac{\partial TC}{\partial Q_t^F} + \frac{\partial AC}{\partial Q_t^F} = \beta \left[\frac{\partial TC}{\partial Q_{t+1}^F} + \frac{\partial AC}{\partial Q_{t+1}^F} \right] \tag{9}$$

Thus, when constraints do not bind, the social planner chooses levels of hydroelectric generation that sets the marginal cost of fossil fuel generation plus the marginal adjustment costs in period t equal to the present value of those costs in period $t+1$.

Suppose the regulator chooses to increase the minimum generation constraint such that it binds in period t but not in period $t+1$. Then, the condition above becomes

$$\frac{\partial TC}{\partial Q_t^F} + \frac{\partial AC}{\partial Q_t^F} = -\lambda_t + \beta \left[\frac{\partial TC}{\partial Q_{t+1}^F} + \frac{\partial AC}{\partial Q_{t+1}^F} \right] \tag{10}$$

This implies the present value of marginal fossil cost plus adjustment costs will be lower in period t than in period $t+1$. Due to the strict convexity of these functions, it must be that total costs increase.

B Additional Background

B.1 Additional requirements of instream flow regulations

Beyond an absolute minimum rate of discharge, instream flow requirements for each dam may also specify additional constraints on the minimum number and duration of substantially increased "pulsed flows" which are likewise a function of the water year type (WYT). An example of these regulations are shown in Table D.1. The primary motivation for pulsed flows are to provide river conditions amenable to certain types of recreation, such as whitewater rafting. However, some aquatic species respond positively to variation in river flows and environmental protection concerns sometimes underlie these requirements as well. Identical to the minimum instream flow requirements, the pulsed flow requirements are categorical, keyed to the WYT, and monotonically increasing in stringency as more water becomes available. These additional requirements similarly reduce the set of allowed discharges for a hydroelectric facility but vary systematically within days and weeks.

The combination of minimum and pulsed instream flow requirements represent a suite of policies which change in concert and increase monotonically in stringency with the WYT. I refer to these requirements jointly as "instream flow requirements" and all estimates represent the cost of the full suite of policies for each WYT.

B.2 Electricity generation technologies

Electricity generation consists of a range of technologies with heterogeneous attributes, each producing a perfectly substitutable output: electricity. Due to the idiosyncrasies of wholesale electricity markets these differing attributes make a combination of generation technologies the lowest-cost way of satisfying demand. From the perspective of a cost-minimizing social planner, many attributes of each generation technology are substitutes. E.g., slightly increasing the intermittency of electricity generation stock would increase the value a social planner would place on non-intermittent resources. As shown in Archsmith et al. (2020), this implies that capacity of disparate generation technologies are complements, rather than substitutes. Understanding the complementary attributes of these technologies merits a brief discussion. I will focus on fossil fuel, nuclear, renewables (such as wind and solar), and hydroelectric, which make up the vast majority of generation capacity.

Fossil fuel-fired generators burn fuels, such as natural gas, to drive turbines either through direct action or through boiling water to make steam. Increasing the level of output at these plants requires increasing the rate of steam production and is costly, compared to steady-state operation. I demonstrate this graphically in Appendix Section D.1. This means that, in periods where plants are rapidly increasing output, they are less efficient in converting fuel into electricity. It is also important to note these plants do not benefit from increased efficiency when ramping down; if anything, plants are also less efficient during the ramp-down phase. This implies increased variability in output will strictly increase fuel consumption as compared to steady-state operation.

Nuclear power also accounts for a substantial portion of the electricity generated in California during the period considered here. Nuclear power plants have very low marginal costs and typically serve "base load" by constantly operating at their rated capacity, shutting down only for refueling, maintenance, or safety reasons. Adjustments to output at nuclear plants are both costly and technically challenging due to the impact of xenon poisoning on reactor operation.

Renewable generation technologies, such as wind and solar photovoltaics, have negligible marginal cost and adjustment costs but the level of output is variable and determined by environmental conditions, not a plant operator. Since output of these generation technologies cannot be increased in response to market conditions, these plants are termed "non-dispatchable". Recall that electricity supply and demand must balance at all times, with the bulk of the adjustments occurring on the supply side. If environmental conditions cause renewable generation to decrease output, such as a cloud passing over a solar array, then other "dispatchable" generation must increase output to compensate.

Hydroelectric dams, in contrast, are dispatchable and face no adjustment costs. Whenever called upon, these dams can with minimal cost and over the course of minutes adjust output between zero and maximum capacity limited only by the quantity of water in their reservoir. Hydroelectric generation is an important component of cost-minimization in a electricity market with heterogeneous generation technologies. As residual demand for dispatchable generation varies, either from changes in demand or changes in the supply of non-dispatchable generation, hydroelectric dams can costlessly adjust output and absorb the variability that would otherwise increase costs at fossil fuel generators.

Variability in demand for fossil fuel generation clearly increases electricity generation costs, as illustrated in Figure D.1. For each hour of weekdays in May of 2015 I compute total demand for fossil fuel electricity generation (in black) and the average quantity of fuel required to produce a MW of electricity, called the heat rate, for fossil fuel generation (in blue) for all facilities in California. Heat rates are the highest – plants are least efficient in converting fuel into energy – when load is rapidly increasing.

C Data and Methods

C.1 Data

This sections provides additional detail beyond the main manuscript.

C.2 Electricity Data

Electricity generation operations details: I obtain measurements of operation status, gross electricity generation, quantity of fuel consumed, and emissions from fuel combustion for every fossil fuel-powered electricity generator with a nameplate capacity of 25 MW or greater from the EPA's Continuous Emissions Monitoring System (CEMS) dataset. These data are available at the generating unit level with hourly resolution from 1997 to the present.

Electricity generator details: EIA Form 860 provides detailed physical characteristics for electricity generators including location (latitude and longitude), ownership, fuel(s) consumed, generating technologies, emissions control technologies, and operating status for all electricity generators with a nameplate capacity of 10 MW or greater. Data provide annual generating-unit detail from 1990 to the present. Additional data on cooling water consumption are available for 2014 and 2018 from the EIA's "Thermoelectric cooling water data".

Fuel consumption and net electricity generation: EIA Forms 923/920/906 provide monthly observations of fuel(s) consumed and net electricity generation for all plants with a nameplate capacity of 50 MW through 2013. After 2013 data are provided annually for all plants, monthly for a random subsample (approximately 1/3 of all plants), with monthly values imputed by the EIA for the remainder.

Electricity price and load: I utilize high-frequency load and price data for electricity supply and demand from the California Independent System Operator (CAISO). These data include hourly load, imports and exports, hourly day-ahead market prices, 15-minute hour-ahead market prices, and 5-minute real-time prices. All load data and pricing data from 1998 through April 1, 2009 provide detail at the zone (NP15) level.[5] Pricing data from April 1, 2009 to the present are available at the node level and also provide aggregation to regions approximating the NP15 zone.

C.2.1 Reconstructed WYI

In its reporting, the California Department of Water Resources (CADWR) rounds the water year index (WYI) to the nearest 0.1 prior to assigning the WYT designation. All analyses presented here account for the effective threshold resulting from this rounding. For example, a WYI of 6.5 or less leads to a designation of "Dry" and over 6.5 to a designation of "Below Normal". Since my calculation of the WYI contains more than two significant digits, I assign values strictly below 6.55 (which round to 6.5 or less) as "Dry" and 6.55 or greater (which round to 6.6 or more) as "Below Normal" to replicate the assignment process used by CADWR.

Values of the reconstructed WYI and the corresponding WYT for each forecast month (February to May) and the end of the water year (October) from 1990 to 2016 are shown in Table D.2.

[5] I am so far unable to obtain electricity prices from early 2003 to the start of 2005. CAISO does not publicly post price data for dates prior to April 1, 2009 and was unable to provide accurate price data in response to my records availability request.

C.2.2 Forecast Accuracy

The February, March, April, and May forecasts from Bulletin 120 appear to be unbiased estimators of actual end-of-year runnoff in the Sacramento Valley. For each forecast month m in year y I estimate the end-of-year water year index (based of actual flow through streamflow monitors) as a function of the current forecast of the the WYI or:

$$WYI_{y,EOY} = \beta_0^m + \beta_1^m WYI_{y,m} + \varepsilon_{y,m} \tag{11}$$

For each regression, Table D.3 shows the estimated slope, intercept, R^2. Columns 4 and 5 show the F-statistic and p-value of a Wald test that the null hypothesis the slope equals one and the intercept equals zero. Columns 6 and 7 show the mean difference and p-value of a paired t-Test of the forecast WYI and end-of-year WYI. The null hypothesis of both tests are implied in the forecast WYI being an unbiased estimator of the end-of-year WYI.

C.3 Methods

C.3.1 Hydroelectric Dam Operations

The specific quantity of electricity generated is a function of turbine efficiency, the quantity of water that passes through the turbines, and the distance between the top of the reservoir and the turbines (the hydraulic head). Since the level of the reservoir changes very little over the course of days, dams choose output at any moment strictly by choosing the quantity of water to discharge.

C.3.2 Measurement of heat rate deviations

The outcome variable of interest in this analysis is heat rate, a measure of efficiency in electricity.[6] Electricity generating units exhibit a range of heat rates when operating under ideal conditions and at peak efficiency.[7] Since the efficiency of electricity generation depends on the mix of generating units actually deployed at a given time, I consider deviations from from the expected heat rate averaged across all units in operation at each point in time.

I compute the system-wide deviation from expected heat rate as follows. For each fossil-fuel powered generating unit (i) in CEMS I compute the average heat rate ($\overline{HR}_{im}$) in each month (m).[8] For a given generating unit, heat rates tend to decrease (improve) over time and may vary systematically throughout the course of the year.[9] Using the monthly-average heat rates, I compute a monthly expected heat rate for the generating unit using plant-specific intercepts and linear time trends.[10]

$$\widehat{HR}_{im} = \beta_0^i + \hat{\beta}_1^i \cdot t \tag{12}$$

[6] A generating unit's heat rate the the quantity of fuel burned, generally measured in millions of British Thermal Units (mmBTU) to standardize across fuels with disparate heat content per unit of weight or volume, divided by the quantity of electricity generated, generally measured in megawatt-hours (MWh). Intuitively, the heat rate is a the amount of energy input required to generate on MWh of electricity output.

[7] For example, a natural gas-powered combustion turbine may have a heat rate around 10 mmBTU/MWh whereas a combined cycle gas turbine may have a heat rate as low as 8 mmBTU/MWh when operating at peak efficiency. The efficiency of electricity generating units has also been systematically increasing over time and may vary throughout the year as well.

[8] For some types of generating units, particularly CCGTs, only a portion of gross electricity generation is reported in CEMS. Using monthly data from Form EIA-860, I scale monthly gross generation reported in CEMS to the total monthly net generation from EIA-860 (which measures all electricity delivered to the grid by each plant). Further details of this adjustment are included in the Appendix.

[9] Identification of the RDD in this context relies substantially on across-year changes in the WYI, consequently, I cannot include plant-level year fixed effects as it would limit identification to only within-year variation in heat rates.

[10] There are a number of possible models for computing expected heat rates. I considered models with polynomial time trends up to order five with and without month-of-year fixed effects, polynomial month-of-year trends up to order 5 with a linear time trend, and month-of-year fixed effects coupled with linear time trends. I evaluated the fit of each model using k-fold cross validation holding out one year of data at a time. The selected model had the best performance (lowest MSE) predicting out of sample and is also one of the more parsimonious models.

Finally, for each hour t plant i is in operation I compute heat rate deviation (HRD_{it}) as the percentage deviation of the plant's actual heat rate from its expected heat rate.

$$HRD_{it} = \frac{HR_{it} - \widehat{HR}_{im}}{\widehat{HR}_{im}} \tag{13}$$

D Results and Robustness

D.1 Fossil fuel generators face adjustment costs

This is illustrated in Figure D.2, which shows the heat rate of two typical natural gas-fired electricity generating units as a function of the change in output level over the previous hour. The heat rate is the quantity of thermal energy, measured in mmBTU, used by a plant to produce one MWh of electricity. Heat rates vary by the technology used for converting fossil fuels into electricity and the specific operating conditions of the plant. Lower values of the heat rate represent more efficient operation.

D.2 Minimum flow policies are binding

One should only expect to see effects of instream flow requirements on efficiency in electricity markets if those requirements are actually binding the decisions of hydroelectric dams. I test whether stream flow below dams changes in response to policy changes using an event study framework. In the simplest case, one would compute average stream flow at times before and after the point where new policy regimes take effect and compare the change in stream flow when the WYT increases, stays the same, or decreases. Releases from hydro units, however, vary systematically with days, within weeks, and over the course of the year. Additionally, the within-stream variation in flow differs substantially across streams and within stream as the total forecast runoff varies. To account for these facts, for each hydro unit i at time t I compute a standardized stream flow with mean zero and standard deviation one ($\bar{F}_{it}$). For each policy change date (e) possible change in the water year type (w) I compute the time since the event (s) and estimate the following regression:

$$\bar{F}_{eis} = \sum_{w \in W} \sum_{s \in S} \beta_{ws} + f_i \left(WYI_{i,e}, WYI_{i,e+1} \right) \tag{14}$$

Where $f_i(\cdot, \cdot)$ is a unit-specific flexible polynomial of the continuous WYI forecast that determines the WYT of both the old and new policy regimes. Figure D.3 plots the β coefficients for increases, no changes, and decreases in WYT. Approximately seven days after new policy regimes take effect deviations from predicted stream flow increase if there was an increase in the WYT, decrease if there was a reduction in the WYT, but stay approximately the same if there was no change in the WYT. These changes are non-trivial in magnitude. Changing the WYT to the next wetter (drier) designation increases (decreases) average daily discharges on the order of 10%.

D.3 Running variable manipulation

A common concern with regression discontinuity designs is manipulation of the running variable. Here the running variable (the WYI) is a function of past rainfall and forecast climatic conditions, which cannot be manipulated by optimizing economic actors. One may be concerned, however, there is pressure placed on the party responsible for generating forecasts that underly the WYI calculation to adjust details so the WYI falls on one side or the other of a WYT threshold. The direction of this hypothetical running variable manipulation is unclear as many parties beyond electricity generators could potentially be impacted by changes in the WYT categorization.[11]

As a preliminary test for manipulation, I examine whether forecasts of the WYI – which are manipulable – are unbiased predictors of the actual WYI measured by streamflow monitors – which is not manipulable. If rainfall

[11]Such manipulation of the running variable could bias the any RDD estimates through two channels. First, if the outcome variable is uncorrelated with the true (and unobserved) value of the running variable, the manipulation of the reported value of the running variable near the discontinuity will tend to bias the estimated treatment effect toward zero. Second, if the decision to (or degree to which) the running variable is manipulated is correlated with the outcome, RDD estimates could be biased in either direction.

forecasts were manipulated with the goal of producing specific states of the WYT, it would cause forecasts to be biased predictors of the realized rainfall at the end of the year. Results in Appendix Section C.2.2 show one cannot reject null hypotheses consistent with each WYI forecast being an unbiased estimator of the end-of-year WYI, computed using only measurements from streamflow monitors.

Next, I consider the density of the WYI forecasts. If the WYI is manipulated so that it will fall on one side or the other of a policy threshold, you would expect the density of the WYI to change discontinuously at that threshold. Figure 3 shows a histogram of WYI values for each month a forecast was issued from 1990 to 2016. In general the density of the WYI appears to vary smoothly across each policy threshold, but it is difficult to draw firm conclusions from merely observing the graph.

As a formal test of running variable manipulation, I deploy statistical tests common in the regression discontinuity design (RDD) literature. For each policy threshold, Table D.4 shows the nonparametric test of differences in density across the threshold proposed by McCrary (2008) for the MSE-minimizing bandwidth choice. In each case, I fail to reject the null hypothesis of running variable manipulation in the vicinity of policy thresholds.[12]

Table D.5 shows these for manipulation of the bandwidth using local polynomial approximations of the density from Calonico et al. (2019) for an array of reasonable bandwidths and the MSE-minimizing bandwidth.[13] I fail to reject the null hypothesis of a discontinuity in the density of the running variable at the policy threshold when using data-driven bandwidth choices.[14]

D.4 Additional RDD results

D.4.1 Robustness

Any RDD requires a number of modeling decisions by the researcher and the designs presented here are no exception. The RDD presented as my primary specification is based on the most reasonable and parsimonious set of modeling choices. However, as a test of the robustness of the specific research design underlying my primary specification, I perturb these choices within a reasonable range and reestimate the RDD, comparing estimates to my primary specification.

The RDD presented as my primary specification is based on the most reasonable and parsimonious set of modeling choices. The estimates above show my results are robust to a range of reasonable bandwidth. However, as a test of the further robustness of the specific research design underlying my primary specification, I perturb other choices within a reasonable range and reestimate the RDD, comparing estimates to my primary specification.

Robustness Test - Exclude covariates: The primary RDD specification treats 28-day periods starting on the second Monday of each month as observations. Observable factors influencing the mean heat rate of plants, for example the total demand for electricity, can vary widely from over time. To improve the precision of my RDD estimates, I include month-of-year fixed effects in my primary specification as described in Calonico et al. (2019). Figure D.4 shows estimates excluding covariates. As expected, the results are of a similar magnitude, but substantially less precise.

[12] I also fail to reject the null hypothesis of no running variable manipulation using the test recommended in Calonico et al. (2019) using local polynomial approximations of the running variable density. These results are presented in Appendix Section D.3.

[13] The data-driven bandwidth selection procedure described in Calonico et al. (2019) sometimes fails to select a bandwidth when data are sparse around the policy threshold. Consequently, I report the results for a range of reasonable bandwidths. There are cases where the the data are too sparse to estimate densities on both sides of the policy threshold. These are denoted by blank cells in Table D.5.

[14] For some large, manually-selected bandwidths, I reject the null of equal densities with a p-value of approximately eight percent. It is important to note these bandwidths are larger than my preferred bandwidth and all of the data-driven automatic bandwidths for estimating effects around the policy discontinuity. Further, the point estimates from tests on the same data with similar bandwidths are correlated and should not be interpreted as independent tests statistical tests.

D.5 Effect on emissions of and damages from local criteria pollutants

The estimates above show instream flow regulations have a deleterious impact on the efficiency of fossil fuel generation participating in the same market, increasing the quantity of fuel consumed to produce each MW of electricity. These increases in fuel consumption will mechanically increase greenhouse gas (GHG) emissions and change the combustion-related emissions of other local criteria pollutants from these plants. Emissions of these pollutants are a significant externality of fossil fuel generation and quantifying their magnitude is important for understanding the true social cost of instream flow requirements.

In Northern California, during the period examined here, all fossil fuel generation utilized natural gas as its fuel source. Combustion of natural gas produces carbon dioxide (CO_2), the principal GHG emitted by fossil fuel plants, in a fixed, stoichiometric proportion. Due to this mechanical relationship between fuel consumption and GHG emissions, my estimates in the previous sections of the impact on fossil fuel consumption can also be interpreted as the change in GHG emissions resulting from instream flow requirements.

Emissions of other local criteria pollutants, such as nitrogen oxides (NO_X) or sulfur dioxide (SO_2), do not follow this mechanical relationship. Further, the local natures of these pollutants are important for considering the social cost of emissions. Each have deleterious impacts in the area surrounding the point of emission, but as they travel away from the point of emission they are diluted, chemically break down, or are precipitated out of the atmosphere, reducing their impact. Thus, the specific location where local criteria pollutants are emitted is important for evaluating the social cost of emissions.

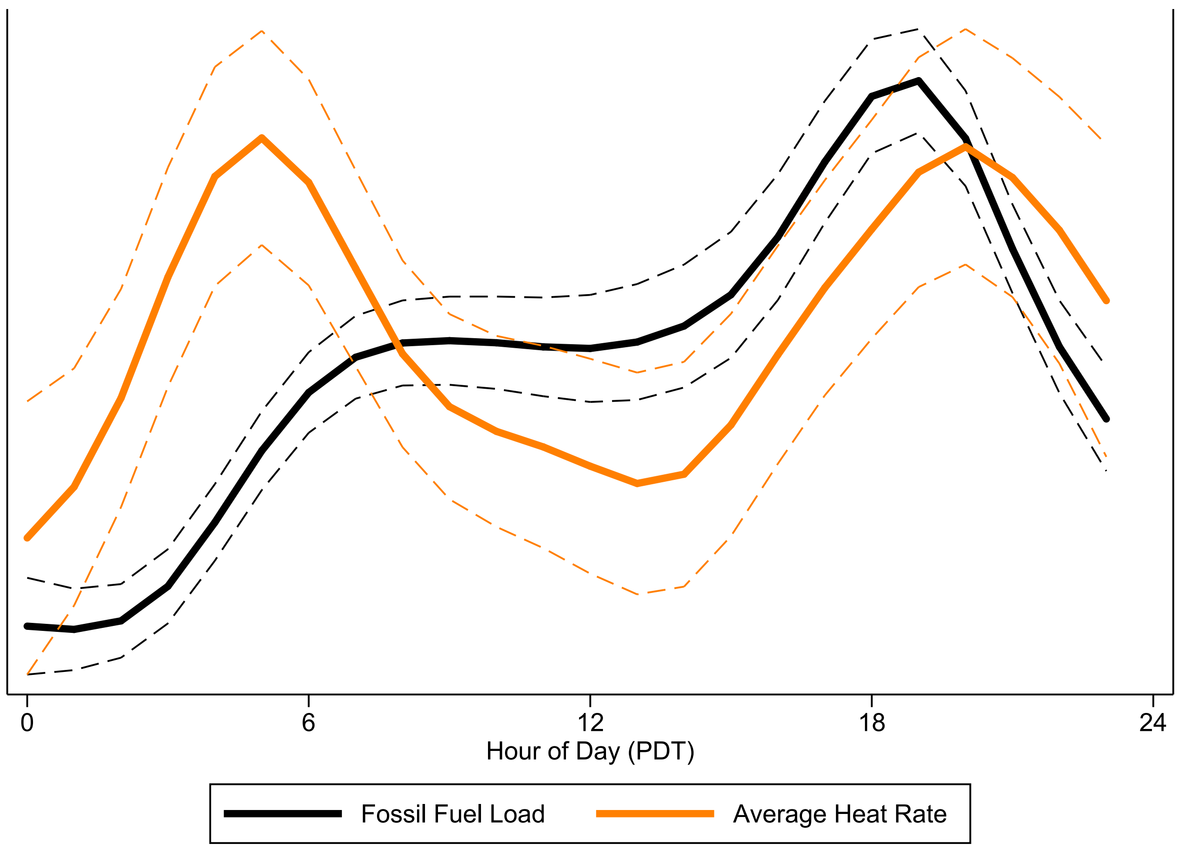
To estimate the social costs related to the emissions of local criteria pollutants, I rely on spatial estimates computed in Muller (2014), which provides a county-level calculation of the marginal damages from NO_X and SO_2 across the United States. For each fossil fuel plant, I observe hourly NO_X and SO_2 emissions to the atmosphere in CEMS. Using these data I can compute the total damages resulting from the emissions of each plant and the product of the marginal damage rate and observed emissions.[15]

Changes in the allocation of electricity generation across fossil fuel plants could have ambiguous effects on the damages from local criteria pollutants. While instream flow policies increase the total quantity of fossil fuels consumed, if production is reallocated to plants with more sophisticated emissions control equipment or to plants farther away from population centers, total damages could decrease. I investigate these effects by estimating the RDD presented in Equation 5 with the emissions rate (quantity of pollution per MW of electricity), average marginal damages, and total damages for each local criteria pollutant as outcomes.

These estimates show substantial increases, between in the total damages from NO_X emissions for the D$\rightarrow$BN and BN$\rightarrow$AN policies, with the principal driving factor being an increase in the quantity of emissions. Instream flow policies have an ambiguous effect on SO_2 damages. Increasing the stringency of instream flow policies tends to increase SO_2 emissions, but there is weak evidence emissions are reallocated to plants with lower marginal damage rates. In the end, the change in SO_2-related damages from each policy are generally statistically indistinguishable from zero.

[15] This requires the reasonable assumption that emissions of local criteria pollutants from each fossil fuel generator are small compared to the total pool of emissions in that region. The bulk of local criteria pollutant emissions come from the operation of automobiles with internal combustion engines, which would not be impacted by the decisions to operate fossil fuel power plants.

Figure D.1: Fossil fuel load and average heat rate in California, May 2015

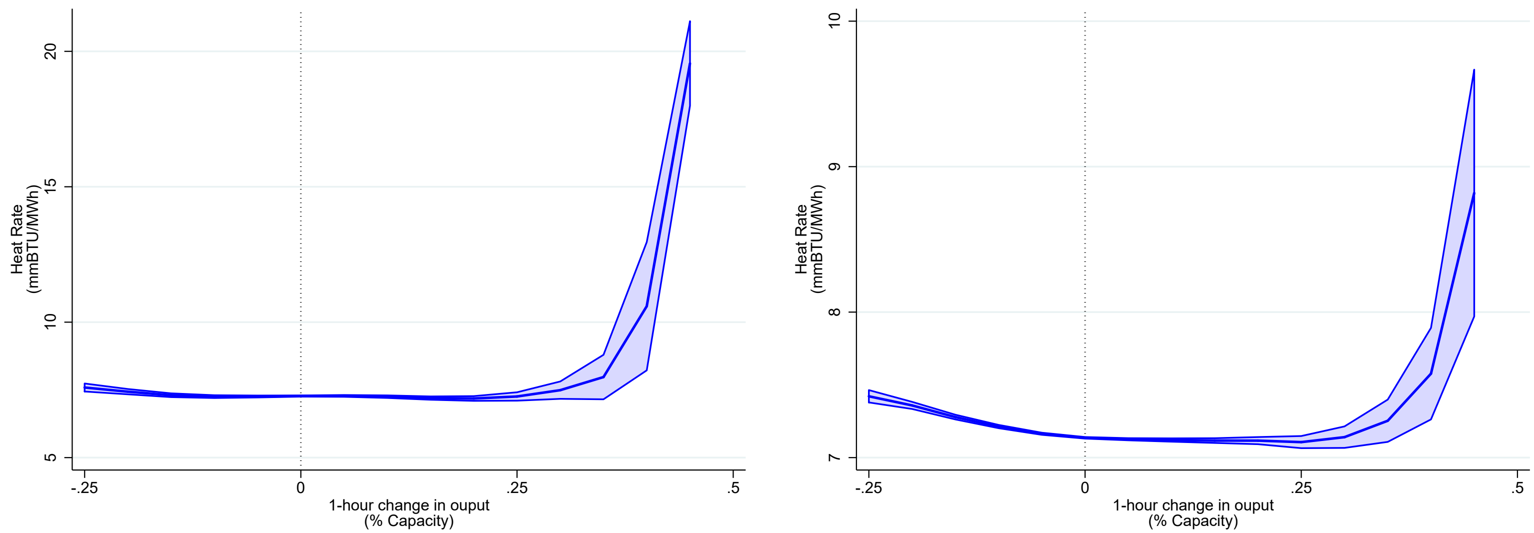


Total fossil fuel load for California from CAISO's Daily Renewables Watch shown in black. Heat rates for all fossil fuel generation in CAISO from CEMS shown in blue. Solid lines are kernel regressions of hourly observations using the Epanechnikov kernel and default data-driven bandwidths. Data limited to weekdays in May of 2015. Pointwise 95% confidence bands shown as dashed lines.

Figure D.2: Heat Rate Profiles for Typical Combined Cycle Gas Turbines

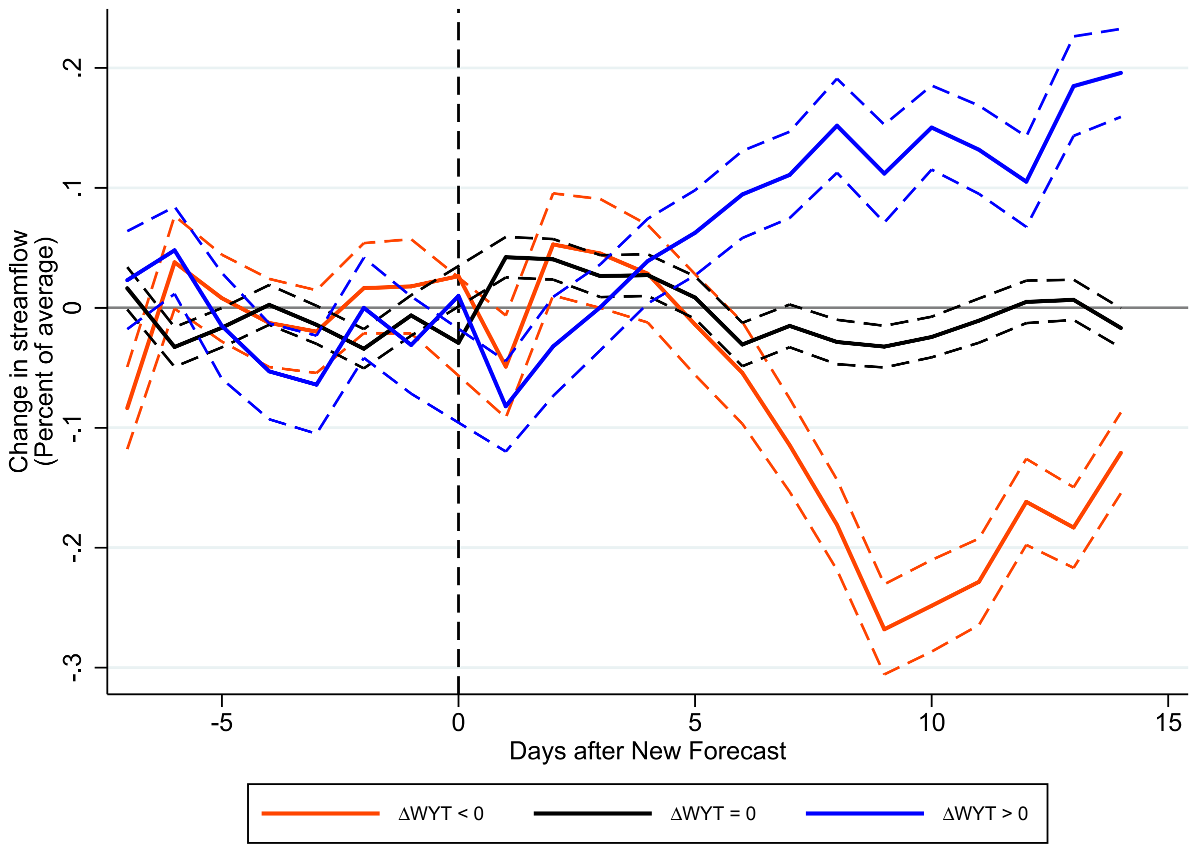
(a) Colusa Generating Station, Unit CT2

(b) Gateway Generating Station, Unit GT1



Local polynomial regression of generator heat rate as a function of the change in output during the previous hour for two CCGTs in CAISO's NP15 region. Based on operational data from CEMS from January 2012 to December 2015. Estimated as 1st-degree polynomials using the Epanechnikov kernel and data-driven bandwidths. Pointwise 95% confidence intervals shown as shaded regions. Estimation limited to periods where the plant is already warm and has been operation for at least five hours.

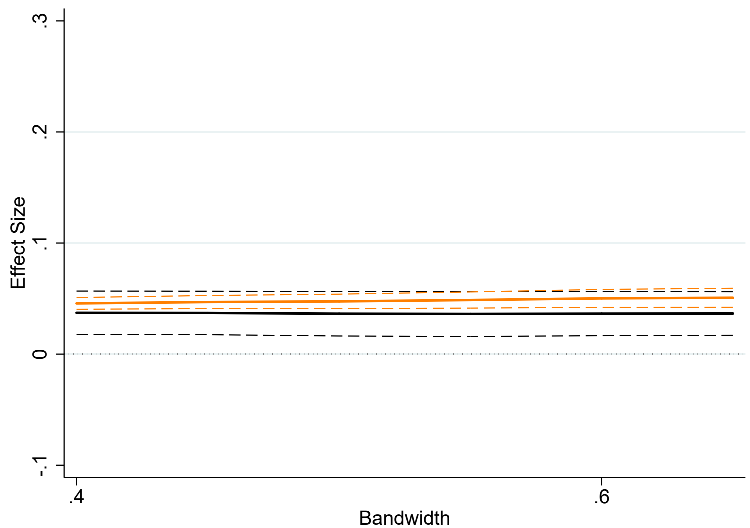
Figure D.3: Event study: Streamflow under changes in water year type (WYT)



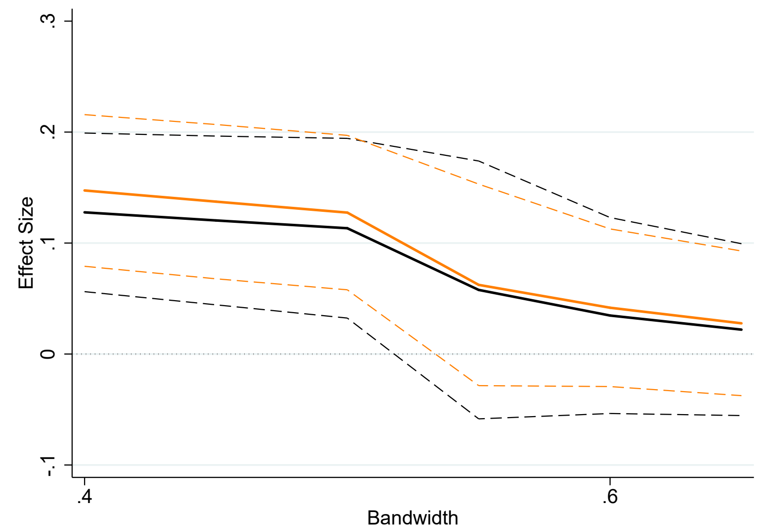
Event study of changes in stream flow in response to changes in minimum flow policies. Policies are set in response to the Water Year Type (WYT). New forecasts underlying the WYT designation are released on day zero. Lines represent deviations from predicted stream flow when the WYT decreases (orange), stays the same (black), or increases (blue). Pointwise 95% confidence intervals robust to arbitrary heteroskedasticity shown in dashed lines.

Figure D.4: Robustness Test: No Covariates

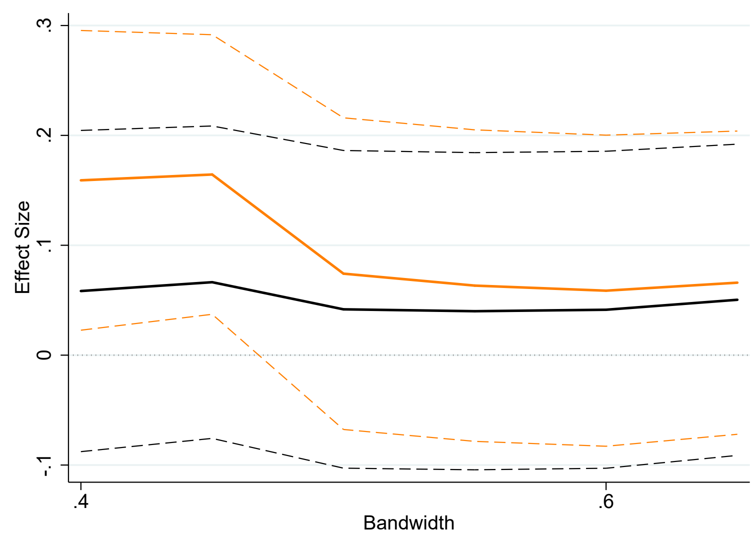
(a) Policy Threshold CD→D



(b) Policy Threshold D→BN



(c) Policy Threshold BN→AN



Robustness test alters the primary specification by excluding covariates (black). Estimates from the primary specification shown in orange for comparison. Estimated effect size by RDD bandwidth. Pointwise 95% confidence intervals shown as dashed lines.

Table D.1: Minimum recreational flows at Chili Bar Dam

Table 4. Minimum Recreational Flow for SF American River below Chili Bar Dam by Water Year Type, Duration and Flow in cfs

Water Year Type	Period	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Critically Dry	March 1 - Friday before Memorial Day	3 Hrs @ 1300	---	---	---	---	3 Hrs @ 1300	3 Hrs @ 1300
	Memorial Day - Labor Day[1]	3 Hrs @ 1300	---	---	3 Hrs @ 1300	3 Hrs @ 1300	5 Hrs @ 1500	5 Hrs @ 1500
	Tuesday after Labor Day - September 30	---	---	---	---	3 Hrs @ 1300	3 Hrs @ 1300	3 Hrs @ 1300
	October 1 - February 28/29	---	---	---	---	---	3 Hrs @ 1300	---
Dry	March 1 - Friday before Memorial Day	3 Hrs @ 1300	3 Hrs @ 1300	---	---	3 Hrs @ 1300	3 Hrs @ 1500	3 Hrs @ 1500
	Memorial Day - Labor Day[1]	3 Hrs @ 1300	3 Hrs @ 1300	---	3 Hrs @ 1300	3 Hrs @ 1300	5 Hrs @ 1500	5 Hrs @ 1500
	Tuesday after Labor Day - September 30	---	---	---	---	3 Hrs @ 1300	3 Hrs @ 1300	3 Hrs @ 1300
	October 1 - February 28/29	---	---	---	---	---	3 Hrs @ 1300	3 Hrs @ 1300
Below Normal	March 1 - Friday before Memorial Day	3 Hrs @ 1300	3 Hrs @ 1300	---	3 Hrs @ 1300	3 Hrs @ 1300	3 Hrs @ 1500	3 Hrs @ 1500
	Memorial Day - Labor Day[1]	3 Hrs @ 1300	3 Hrs @ 1300	---	3 Hrs @ 1300	3 Hrs @ 1300	6 Hrs @ 1500	6 Hrs @ 1500
	Tuesday after Labor Day - September 30	---	---	---	3 Hrs @ 1300	3 Hrs @ 1300	3 Hrs @ 1500	3 Hrs @ 1500
	October 1 - 31	3 Hrs @ 1300	---	---	---	3 Hrs @ 1300	3 Hrs @ 1500	3 Hrs @ 1500
	November 1 - February 28/29	---	---	---	---	---	3 Hrs @ 1300	3 Hrs @ 1300
Above Normal	March 1 - Friday before Memorial Day	3 Hrs @ 1300	3 Hrs @ 1300	3 Hrs @ 1300	3 Hrs @ 1300	3 Hrs @ 1300	4 Hrs @ 1750	4 Hrs @ 1750
	Memorial Day - Labor Day[1]	3 Hrs @ 1500	3 Hrs @ 1500	3 Hrs @ 1500	3 Hrs @ 1500	3 Hrs @ 1500	6 Hrs @ 1750	6 Hrs @ 1750
	Tuesday after Labor Day - September 30	---	---	---	3 Hrs @ 1500	3 Hrs @ 1500	3 Hrs @ 1500	3 Hrs @ 1500
	October 1 - 31	3 Hrs @ 1300	---	---	---	3 Hrs @ 1300	3 Hrs @ 1500	3 Hrs @ 1500
	November 1 - February 28/29	---	---	---	---	---	3 Hrs @ 1500	3 Hrs @ 1500
Wet	March 1 - Friday before Memorial Day	3 Hrs @ 1500	3 Hrs @ 1500	3 Hrs @ 1500	3 Hrs @ 1500	3 Hrs @ 1500	6 Hrs @ 1750	6 Hrs @ 1750
	Memorial Day - Labor Day[1]	4 Hrs @ 1500	4 Hrs @ 1500	4 Hrs @ 1500	4 Hrs @ 1500	4 Hrs @ 1500	6 Hrs @ 1750	6 Hrs @ 1750
	Tuesday after Labor Day - September 30	---	---	---	3 Hrs @ 1500	3 Hrs @ 1500	3 Hrs @ 1500	3 Hrs @ 1500
	October 1 - 31	3 Hrs @ 1300	---	---	---	3 Hrs @ 1300	3 Hrs @ 1500	3 Hrs @ 1500
	November 1 - February 28/29	---	---	---	---	---	3 Hrs @ 1500	3 Hrs @ 1500

[1] The "Memorial Day – Labor Day" period refers to Saturday of Memorial Day weekend through Monday of Labor Day weekend.

Source: Federal Energy Regulatory Commission, Order Issuing New License, Pacific Gas & Electric Company Project 2155-024, August 20, 2014. Excludes minimum discharges under the super critical dry designation can only occur after multiple years of critical dry designations.

Table D.2: Reconstructed WYI and WYT by month 1990 to 2016

(a) 1990 - 1996

Year	Month	WYI	WYT
1990	Feb	5.282	C
1990	Mar	4.995	C
1990	Apr	4.545	C
1990	May	4.397	C
1990	Oct	4.810	C
1991	Feb	3.564	C
1991	Mar	3.148	C
1991	Apr	4.432	C
1991	May	4.304	C
1991	Oct	4.210	C
1992	Feb	3.838	C
1992	Mar	4.532	C
1992	Apr	4.310	C
1992	May	4.246	C
1992	Oct	4.060	C
1993	Feb	7.306	BN
1993	Mar	8.017	AN
1993	Apr	8.210	AN
1993	May	8.370	AN
1993	Oct	8.540	AN
1994	Feb	5.787	D
1994	Mar	5.944	D
1994	Apr	5.278	C
1994	May	5.091	C
1994	Oct	5.020	C
1995	Feb	9.550	W
1995	Mar	8.672	AN
1995	Apr	11.409	W
1995	May	12.397	W
1995	Oct	12.890	W
1996	Feb	7.461	BN
1996	Mar	9.375	W
1996	Apr	9.384	W
1996	May	9.708	W
1996	Oct	10.260	W

(b) 1997 - 2003

Year	Month	WYI	WYT
1997	Feb	13.338	W
1997	Mar	11.458	W
1997	Apr	11.293	W
1997	May	11.005	W
1997	Oct	10.820	W
1998	Feb	9.581	W
1998	Mar	12.333	W
1998	Apr	12.171	W
1998	May	12.361	W
1998	Oct	13.310	W
1999	Feb	8.837	AN
1999	Mar	10.282	W
1999	Apr	10.073	W
1999	May	10.044	W
1999	Oct	9.800	W
2000	Feb	7.863	AN
2000	Mar	9.525	W
2000	Apr	9.229	W
2000	May	9.229	W
2000	Oct	8.940	AN
2001	Feb	5.986	D
2001	Mar	6.278	D
2001	Apr	5.811	D
2001	May	5.871	D
2001	Oct	5.760	D
2002	Feb	7.404	BN
2002	Mar	6.795	BN
2002	Apr	6.727	BN
2002	May	6.503	D
2002	Oct	6.350	D
2003	Feb	7.904	AN
2003	Mar	7.047	BN
2003	Apr	7.172	BN
2003	May	8.036	AN
2003	Oct	8.210	AN

Table continued on next page.

Table D.2: Reconstructed WYI and WYT by month 1990 to 2016 (continued)

(c) 2004 - 2010

Year	Month	WYI	WYT
2004	Feb	7.709	BN
2004	Mar	8.546	AN
2004	Apr	8.021	AN
2004	May	7.681	BN
2004	Oct	7.510	BN
2005	Feb	7.400	BN
2005	Mar	6.866	BN
2005	Apr	7.351	BN
2005	May	7.395	BN
2005	Oct	8.490	AN
2006	Feb	9.770	W
2006	Mar	9.965	W
2006	Apr	11.383	W
2006	May	13.023	W
2006	Oct	13.200	W
2007	Feb	6.383	D
2007	Mar	6.911	BN
2007	Apr	6.303	D
2007	May	6.199	D
2007	Oct	6.190	D
2008	Feb	6.304	D
2008	Mar	6.318	D
2008	Apr	5.724	D
2008	May	5.396	C
2008	Oct	5.160	C
2009	Feb	4.644	C
2009	Mar	5.128	C
2009	Apr	5.672	D
2009	May	5.489	D
2009	Oct	5.780	D
2010	Feb	6.546	D
2010	Mar	6.287	D
2010	Apr	6.257	D
2010	May	6.881	BN
2010	Oct	7.080	BN

(d) 2011 - 2016

Year	Month	WYI	WYT
2011	Feb	7.856	AN
2011	Mar	7.727	BN
2011	Apr	9.981	W
2011	May	10.022	W
2011	Oct	10.540	W
2012	Feb	5.986	D
2012	Mar	5.465	D
2012	Apr	6.416	D
2012	May	6.861	BN
2012	Oct	6.890	BN
2013	Feb	7.546	BN
2013	Mar	6.393	D
2013	Apr	6.014	D
2013	May	5.790	D
2013	Oct	5.830	D
2014	Feb	3.731	C
2014	Mar	3.839	C
2014	Apr	4.143	C
2014	May	4.019	C
2014	Oct	4.070	C
2015	Feb	5.127	C
2015	Mar	4.713	C
2015	Apr	4.137	C
2015	May	3.965	C
2015	Oct	4.010	C
2016	Feb	6.497	D
2016	Mar	6.122	D
2016	Apr	7.262	BN
2016	May	7.115	BN

WYI and WYT for the Sacramento Valley reconstructed from forecasts in CADWR Bulletin 120 (Feb - May) or actual measured runoff (Nov) then the formula specified by CADWR. Replicating methods used by CADWR, the WYT designation is computed by first rounding WYI to the nearest 0.1 then applying policy thresholds shown in the main paper.

Table D.3: Regression estimates of WYI forecast accuracy

	Coefficients			Wald Test		Paired t-Test	
	Slope	Intercept	R^2	F-stat	p-value	Difference	p-value
Forecast Month	(1)	(2)	(3)	(4)	(5)	(6)	(7)
February	1.10	-0.09	0.63	1.93	0.17	-0.58	0.08
	(0.30)	(2.04)					
March	1.10	-0.23	0.74	1.31	0.29	-0.43	0.13
	(0.12)	(0.80)					
April	1.13	-0.71	0.95	2.98	0.07	-0.24	0.08
	(0.06)	(0.41)					
May	1.05	-0.21	0.98	2.35	0.12	-0.13	0.07
	(0.03)	(0.19)					

Regressions of the final end-of-year WYI on the forecast WYI by month. Standard errors robust to arbitrary heteroskedasticity shown in parentheses. Columns 4 and 5 show the F-statistic and p-value of a Wald test that the null hypothesis the slope equals one and the intercept equals zero. Columns 6 and 7 show the mean difference and p-value of a paired t-Test of the forecast WYI and end-of-year WYI. The null hypothesis of both tests are implied in the forecast WYI being an unbiased estimator of the end-of-year WYI.

Table D.4: Test of running variable manipulation (McCrary)

Policy Threshold Name	WYI	Obs. Left	Obs. Right	McCrary Bandwidth	t-stat	p-value
CD → D	5.4	37	31	0.359	0.16	0.873
D → BN	6.5	31	25	0.291	-0.00	1.000
BN → AN	7.8	25	15	0.252	0.50	0.619
AN → W	9.1	15	37	0.727	0.66	0.508

Test of running variable manipulation using data-driven bandwidth selection from McCrary (2008) at each policy threshold. WYI from CADWR forecasts released in February, March, April, and May from 1990 to 2016.

Table D.5: Test of Running Variable Manipulation (**calonico2016regression**)

Policy Threshold (WYI)	CD → D 5.4	D → BN 6.5	BN → AN 7.8	AN → W 9.2
Bandwidth 0.3				
Bandwidth 0.4	-0.772	-0.808	0.410	
	(0.440)	(0.419)	(0.681)	
Bandwidth 0.5	-0.790	-0.881	0.520	
	(0.429)	(0.378)	(0.603)	
Bandwidth 0.6	-1.074	-1.313	0.759	
	(0.283)	(0.189)	(0.448)	
Bandwidth 0.7	-0.932	-1.331	0.771	0.839
	(0.352)	(0.183)	(0.441)	(0.402)
Bandwidth 0.8	-0.552	-1.222	0.481	0.904
	(0.581)	(0.222)	(0.630)	(0.366)
Bandwidth 0.9	-0.320	-1.048	0.268	0.843
	(0.749)	(0.295)	(0.789)	(0.399)
Bandwidth 1.0	-0.352	-0.985	0.002	0.722
	(0.725)	(0.325)	(0.999)	(0.470)
MSE-min Bandwidth	-0.556	-1.023	0.353	0.768
	(0.578)	(0.306)	(0.724)	(0.443)
Selected Bandwidth	0.80	1.11	0.85	0.63

Test of running variable manipulation from **calonico2016regression** using local linear density estimators at each policy threshold for the specified bandwidth. WYI from CADWR forecasts released in February, March, April, and May from 1990 to 2016. MSE-min bandwidth selects an MSE-optimal bandwidth as the smallest of the bandwidth which minimizes the MSE difference of the two densities and the bandwidth which minimizes the MSE of the sum of densities. Nonparametric local linear densities estimated using the triangle kernel assuming the CDF on each side of the threshold have equal higher-order derivatives. This data-driven bandwidth selection procedure described in Calonico et al. (2019) sometimes fails to select an optimal bandwidth. Consequently, I report the results for a range of reasonable bandwidths. There are cases where the the data are too sparse to estimate densities on both sides of the policy threshold. These are denoted by blank cells.

Table D.6: Effect of instream flow requirements on NO_X emissions and damages

(a) NO_X Emissions Rate

	CD→D	D→BN	BN→AN
log NO_X Emissions Rate (ton/MWh)	0.028	4.887	1.620
	(0.076)	(0.741)***	(0.787)**
RD Bandwidth	0.400	0.400	0.400

(b) NO_X Average Marginal Damages

	CD→D	D→BN	BN→AN
log NO_X Marginal Damages ($/ton)	-0.038	0.129	0.020
	(0.008)***	(0.058)**	(0.042)
RD Bandwidth	0.400	0.400	0.400

(c) NO_X Total Damages per MWh

	CD→D	D→BN	BN→AN
log NO_X Total Damages ($/MWh)	0.104	3.807	1.549
	(0.046)**	(0.778)***	(0.440)***
RD Bandwidth	0.400	0.400	0.400

Each panel shows the effect of the specified instream flow policy change on the mean system-wide log mean NO_X emissions using the RDD described in the main paper. Panel (a) shows the effect on the emissions rate (in tons per MWh of electricity generated). Panel (b) shows the quantity-weighted mean marginal damages per ton of emissions using county-level marginal damages from Muller (2014). Panel (c) shows the mean damages per MWh of electricity generated. 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 D.7: Effect of instream flow requirements on SO_2 emissions and damages

(a) SO_2 Emissions Rate

	CD→D	D→BN	BN→AN
log SO_2 Emissions Rate (ton/MWh)	0.031	0.395	0.184
	(0.009)***	(0.024)***	(0.131)
RD Bandwidth	0.400	0.400	0.400

(b) SO_2 Average Marginal Damages

	CD→D	D→BN	BN→AN
log SO_2 Marginal Damages ($/ton)	0.064	0.169	-0.105
	(0.009)***	(0.093)*	(0.085)
RD Bandwidth	0.400	0.400	0.400

(c) SO_2 Total Damages per MWh

	CD→D	D→BN	BN→AN
log SO_2 Total Damages ($/MWh)	0.195	-0.287	0.209
	(0.017)***	(0.159)*	(0.183)
RD Bandwidth	0.400	0.400	0.400

Each panel shows the effect of the specified instream flow policy change on the mean system-wide log mean SO_2 emissions using the RDD described in the main paper. Panel (a) shows the effect on the emissions rate (in tons per MWh of electricity generated). Panel (b) shows the quantity-weighted mean marginal damages per ton of emissions using county-level marginal damages from Muller (2014). Panel (c) shows the mean damages per MWh of electricity generated. 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