Dam Spillovers: Direct costs and spillovers from environmental constraints on hydroelectric generation*

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Abstract

Water policy, and particularly, its interaction with energy supply and demand are at the forefront of currently policy analysis. This paper contributes to that discussion by estimating the direct costs from a set of environmental regulations on hydroelectric dams and the resulting indirect costs to unregulated fossil fuel generators participating in the same output market using micro-level data and accounting for firm-level heterogeneity. Using a novel method of imputing hour-to-hour operations at hydroelectric dams, I find large direct effects, reducing the mean value of output between 10.6 and 18.0%. However, substantial spillovers to other firms comprise over 50% of the total estimated cost of the regulations. Difference-in-difference estimates typical in the literature are likely to vastly understate direct costs and spillovers. Decomposition of these effects suggests spillovers are driven by water scarcity in dry years and complementarity between disparate generation technologies in wetter years. These effects will continue to grow as climate change increases water scarcity and the deployment of renewable generation technologies increases.

JEL: L51, Q25, Q51, Q52, Q53

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1 Introduction

Assessing the costs of regulation is a central question in public policy. Economists, in particular, have invested substantial effort toward quantifying the impacts on costs, efficiency, and output for firms bound by regulation (e.g., Gray [1987] or Greenstone et al. [2012]). These regulated firms, however, may participate in both input and output markets alongside other actors facing different regulatory constraints. Examples are numerous; environmental regulations, tax and employment laws, and reporting requirements include exemptions conditional on firm size, location, or other attributes. Strategic behavior by regulated firms can affect supply and demand in input and output markets, altering the profit-maximizing decisions of both regulated firms and their unregulated counterparts participating in connected markets.

Understanding the magnitude of these spillovers is important for several reasons. First, to the extent productivity of the regulated and unregulated firms are positively (negatively) correlated, directing accounting ignoring spillovers will under (over)-state the true costs of regulation. Second, empirical estimates using unregulated firms affected by regulatory spillovers as controls will tend to under (over)-state costs when productivity of regulated and unregulated firms are positively (negatively) correlated. This differences-in-differences approach is common in literature estimating the costs of regulation or efficiencies of regulatory reform.

In this paper I consider the impacts of a set of environmental regulations, in the form of restrictions on stream flow downstream from hydroelectric dams, on the efficiency of electricity generation. First, I find the obvious result, more stringent regulations reduce the economic value of electricity generated by hydroelectric dams between 10.6% and 18.0%, as they are constrained away from the profit-maximizing allocation of generation through time. This allocative inefficiency spills over to other electricity generators, increasing fuel consumption at fossil fuel plants, who are not directly constrained by streamflow regulations, between 6.8% and 9.0% per unit of electricity generated. As fossil fuel generation accounts for a larger portion of the market, over 50% of the social costs of the regulations are a result of spillovers. All told, inefficiencies resulting from these regulations impose social costs between \$63.9 and \$78.1 million per year these policies are in effect.

This paper makes a number of contributions to the empirical literature estimating costs of regulation and spillovers. First, I exploit unique variation in the stringency of regulation to estimate the impacts of a set of environmental policies on firm productivity using credible identification strategies without structural assumptions. Second, I utilize this same policy variation to precisely estimate substantial, positively-correlated spillovers to firms participating in the same output markets but unencumbered by these regulations. I compute spillovers using micro-level data, accounting for firm-level heterogeneity. Finally, I impute electricity generation at high-frequency from hydroelectric dams, which have to this point received relatively little attention in the literature.

Analysis of the impacts of regulation on firm productivity face a number of empirical challenges. Foremost amongst these concerns, plants with older capital stock are more likely to require compliance expenditures but are also likely to be less productive. This heterogeneity bias overstates the productivity costs of abatement. Recent empirical estimates of the impacts of regulation on productivity rely on firm-level productivity and panel data methods to account for firm-level heterogeneity. Gray and Shadbegian [1995] examine a panel of paper mills, oil refineries, and steel mills and find firms with larger abatement expenditures suffer losses in productivity between 35% and 228% in excess of abatement costs when looking across plants, but very little effect of abatement on productivity when looking within plants over time. Berman and Bui [2001] find large capital expenditures but only transient reductions in productivity at oil refineries complying with air quality standards in the Los Angeles Basin compared to refineries in other locations absent strict regulations. Their conclusion is accounting measures of abatement costs, such as PACE, vastly overstate true abatement costs.

There is a broad literature examining the costs of regulation in the electricity industry. A substantial vein examines efficiency effects in the transition from the transition cost-of-service regulation to competitive markets for generation or retailing of electricity, frequently employing a differences-in-differences approach to identification. Bushnell and Wolfram [2005] estimate changes in the operating efficiency, measured using heat rates, of electricity generating plants divested after cost-of-service regulatory reforms. They find changes in incentives, either through divestment or regulatory reform, led to efficiency improvements of approximately 2% with changes in ownership having little additional effect. Cicala [2014] examines the effect of regulatory reforms on coal and natural gas procurement at fossil fuel-powered electricity generators. Using a matched differences-in-differences approach he finds coal plants transitioning from cost-of-service regulation to deregulated markers reduced fuel procurement costs between 12 and 13%. Natural gas generators, using a homogeneous input with more transparent pricing, saw little change in fuel procurement costs. Craig and Savage [2013] estimate the effect of wholesale and retail market reforms using state-level differences-in-differences with additional controls to account for selective entry and attrition. They find wholesale deregulation had little impact on thermal efficiency whereas the combination of wholesale and retail market reforms led to efficiency improvements of approximately 9%. Further, they find these thermal efficiency improvements spill over to municipally-owned plants operating in states with deregulated markets. Fabrizio et al. [2007] likewise exploit variation in the timing of regulatory reforms across states to estimate the impact of those reforms on inputs to electricity generation including fuel and labor. The find regulatory reforms lead to an approximate 3% decrease in employment, a 9% reduction in non-fuel expenses but no change in fuel-related expenditures. In each case, these researchers control for time-varying effects common across all generators using comparable generators for who the regulatory environment did not change as a control group. If, however, there are positive (negative) spillovers from the treated generators to the controls, these difference-in-difference estimators will under (over)-state the efficiency gains from market liberalization.

The costs and incidence of environmental regulations on electricity generation are also frequently examined. Mansur [2001] measures inefficiencies in electricity generation after coincident implementation of market restructuring and new air quality regulations. He finds abatement costs exceeded the competitive level by approximately 8%, likely due to the exercise of market power.

The focus of this paper is on the relationship policy-induced changes in the behavior of dams and outcomes in electricity markets. There is, however, a recent and growing literature examines the relationship between climate-induced water scarcity and electricity generation. Eyer and Wichman [2016] find increased water scarcity, measured by the Palmer Drought Severity Index (PDSI), leads to reduced hydroelectric generation and increased fossil fuel generation, particularly at natural gas plants. Many others (e.g., Lofman and Petersen [2002], Ackerman and Fisher [2013], Scanlon et al. [2013]) note the direct effect of water scarcity on availability of cooling water for fossil fuel generation. This relationship poses challenges to estimating productivity effects which are addressed by the empirical methods in this paper.

This paper proceeds with additional background on regulation and the research setting in Section 2. Data used in the analyses are described in Section 3. Section 4 discusses challenges to identifying efficiency costs and spillovers resulting from these policies. Empirical estimates of the effects of these policies are presented in Section 5. Section 6 concludes with a discussion of the implications for policy and analysis.

2 Background

2.1 Environmental regulations on hydroelectric generation

In this paper I consider environmental regulations on hydroelectric dams in the Sacramento Valley of Northern California. This region contains the largest hydroelectric facilities California and produces the majority of the state's hydroelectric power. Figure 2 shows the location of large hydroelectric facilities and fossil fuel generators in the state of California. Hydroelectric dams continuously make decisions on the quantity of water to discharge through their turbines for generating electricity. Once discharged, this water flows through a waterway downstream of the dam. 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. These constraints have diverse goals including flood management, supporting habitat for fish and wildlife, replicating natural flow rates, maintaining water supplies, and recreation.[1] In particular, these dams must follow a schedule 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.[2] 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 number of outcomes in the electricity generation markets.

For all major hydroelectric dams in the Sacramento Valley, minimum flow requirements 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).[3] The particular designation of the WYT is determined by an index of total unimpaired runoff from drainage basin called the "Water Year Index" (WYI). The California Department of Water Resources (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 1.[4]

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

The WYT, which in turn determines the level of minimum flow required downstream of each dam,

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

[2] 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.

[3] Regulations covering some dams also specify an additional water year type of "Extreme Critical Dry" for extremely dry years after a string of critically dry years. As described in Section 4 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.

[4] The 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).

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.[5] These forecasts are issued and the WYT designation changes four times per year (generally on the first Monday) in February, March, April, and May and become binding within three to seven days. Additionally, the WYT is updated using realized flow through the river, as measured by stream flow gages, at the end of the water year on October 1.

As an example, the minimum flow requirements downstream of the Loon Lake Dam are shown in Figure 1a.[6] Figure 1b shows these policies graphically. Each dam may also face additional constraints specifying a minimum number and duration of substantially increased "pulsed flows" which likewise are a function of the WYT. An example of these regulations are shown in Table 2.[7] There are some important facts to note. First, 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.

Second, 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. 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.[8] 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.[9] Larger minimum flow restrictions, 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 restrictions.

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[5]The CADWR rounds the WYI from Equation 1 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, Table 1 specifies 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.

[6]My research has revealed similar minimum flow constraints based on the WYT in the operating licensees of other dams in the Sacramento Valley.

[7]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.

[8]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.

[9]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.

2.2 Spillovers to other electricity generation are likely

Regulations on hydroelectric facilities are a case where one may expect to see substantial, positively-correlated spillovers to other market participants. First, the minimum flow policies examined here 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 et al. [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.

Additionally, during the period examined here, electricity generation consists of a range of technologies with quite heterogeneous attributes. Of particular interest in this case are fossil fuel generation, renewables (such as wind and solar), and hydroelectric dams. 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. This is illustrated in Figure 3, 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.[10] Clearly, in periods where plants are rapidly increasing output, they are less efficient in converting fuel into electricity.[11]

Renewable generation technologies, such as wind and solar photovoltaics, face negligible adjustment costs but the level output is variable and determined by environmental conditions, not a plant operator. Hydroelectric dams face neither of these constraints. 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.[12]

Many idiosyncratic attributes of electricity markets combine to exacerbate the likelihood of spillovers. Electricity demand varies substantially throughout the course of the day. Many renewable generation technologies, such as wind and solar PV are "non-dispatchable" – their ability to produce electricity is a function of only environmental conditions and are unable to adjust output on command. Proper function of the electricity grid requires supply and demand must balance at all times and large-scale storage across time is economically infeasible. Finally, the bulk of end consumers pay a fixed retail rate for each unit of electricity consumed and price signals from the generation market are not communicated to end consumers leading to near-perfectly inelastic demand. The combination of these factors, means reactions to changes in supply and demand must all occur on the supply side with dispatchable generators, generally fossil fuel and hydroelectric plants, adjusting their output in real time to match demand.

While hydroelectric facilities can adjust output with little or no cost, fossil fuel generation faces non-trivial adjustment costs, variability in demand for fossil fuel generation tends to increase costs, as illustrated in Figure 3c. For each hour of weekdays in May of 2015 I compute total demand for fossil fuel electricity

[10] 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.

[11] 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 as well. This implies increased variability in output will strictly increase fuel consumption as compared to steady-state operation.

[12] 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.

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 increasing.

In light of this, hydroelectric dams, renewables, and fossil fuel generation are complementary. In periods when demand is increasing quickly hydroelectric dams can rapidly increase output, decreasing adjustment costs as fossil fuel generation ramps up. 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 the regulations place no constraints on the behavior of fossil fuel generators.

3 Data

3.1 Electricity Data

I have compiled and integrated a wide set of data on the capital stock and operation of electricity generating units, commonly used in the analysis of electricity markets. These data are described briefly here. Further details on assembling the data and matching information across the disparate sources are provided in the the Online Appendix.

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 (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 2015 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), and imputed monthly 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.[13] 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.

3.2 Hydrological Data

CADWR Forecasts and Runoff: I obtain information on historical hydrological conditions from the California Department of Water Resources (CADWR) Bulletin 120. In particular, every February, March, April, and May the CADWR releases a forecast of total unimpaired runoff in the Sacramento Valley for the current water year.[14] These forecasts are used to compute a numeric index of total unimpaired runoff, the Water Year Index (WYI), and a categorical designation of the level of runoff, the Water Year Type (WYT).[15] 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 available on the CADWR website. Using information from tables in these forecasts, I compute the numeric WYI for each monthly forecast using the formula in Equation 1 and assign the corresponding WYT in effect after that forecast.[16]

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.[17]

Hourly Streamflow and Hydroelectric Dam Operations: Previous research using high-frequency, plant-level electricity generation data rely on the CEMS dataset described above.[18] These data are limited to electricity generators reporting into the US EPA's Air Markets Program and, by definition, exclude hydroelectric generators. I reliably impute hourly electricity generation for the bulk of large hydroelectric dams in California using only public-available data. This process combines data from a range of sources and is described in detail in the Online Appendix but is briefly described below.

The operating licenses of most major hydroelectric dams require the dam to maintain flow through downstream waterways within specified ranges. Ensuring compliance with these downstream flow constraints requires monitoring. Data from these stream flow monitors are made available through the CADWR's Data Exchange Center and the US Geological Survey's National Water Information System. Dams generate electricity by discharging water from their reservoirs through turbines. The quantity of electricity generated

[13] 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.

[14] The CADWR water year starts with the beginning of the rainy season and runs from October through September of the the following year.

[15] These WYT categories are critically dry (CD), dry (D), below normal (BN), above normal (AN), and wet (W).

[16] The full list of reconstructed WYI values and WYT designations is shown in Table A.1 in the Appendix.

[17] 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 in the regression discontinuity design described later.

[18] Economic analysis of electricity markets have relied on high-frequency data from CEMS since at least Joskow and Kahn [2002]. The bulk of these analyses lack information on the hour-to-hour operations of hydroelectric facilities and are forced to make assumptions on their short-term behavior.

is a simple function of the volume of water passing through the turbines and the distance the water falls (which is a function of reservoir height). The reservoir height is relatively stable over time, so to increase electricity generation dams must increase the volume of water discharged, which will be recorded by downstream flow monitors. Combining hourly observations of stream flow and monthly discharges and net generation, I am able to impute hourly generation for all dams with downstream flow monitors.[19,20]

4 Identification

In the present research, I am interested in determining the impact of minimum flow regulations tied to each specific WYT, a treatment I will term $d \in \{CD, D, BN, AN, W\}$, on some outcome of interest, which I will term Y. In any empirical exercise using observational data, it is useful to first consider how an omnipotent researcher would design a randomized experiment to determine the effect of interest. 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 the local average treatment effect of the changing the policy from, e.g., CD to D would be:

$$\beta_{CD,D} = E[Y_{it}|d_{it} = D] - E[Y_{it}|d_{it} = CD] \tag{2}$$

Clearly, such an 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. First, the WYI is a reasonable proxy for the sum total of water available for discharge at hydroelectric dams in the Sacramento Valley. To this point, Eyer and Wichman [2016] 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. This implies there will be systematically less electricity derived from hydropower when the WYI is lower and minimum flow requirements are less restrictive. Failing to account for the between the WYI and total hydroelectric generation could conflate effects of the policy with impacts of water scarcity unrelated to the policy.[21]

Second, while the nature of the policy variation means minimum flow policies change frequently over time, these policies are not exogenously assigned. Namely, the prevailing WYT is a function of the quantity

[19] I am able to obtain actual daily generation for a set of large hydroelectric dams in the Western US. In the Online Appendix I demonstrate imputed generation predicts actual generation with an R^2 of at least 0.983 and median absolute error of 1.8% or less.

[20] Dams may at times, e.g., after periods of heavy precipitation upstream, may elect to discharge more water than can flow through the powerhouse by utilizing a spillway or opening floodgates. I additionally analyze the discharge from dams over time to identify periods where dams are "spilling" water and adjust imputed output down to the rated generating capacity of the dams turbines.

[21] 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.

of past and forecast future precipitation in the hydrologic basin measured by the WYI. It is clear the WYI is correlated with myriad unobservables that may affect the efficiency of fossil fuel generation.[22] Any credible estimate of the impact of minimum flow restrictions must address for this omitted variables bias.

Next, 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.

4.1 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 1b 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 the matched differences-in-differences identification of the causal impact of minimum flow policies. A difference-in-difference estimate could control for idiosyncratic effects using the same plant at different times as a control. While the matching algorithm selects 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.[23] 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.

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$\rightarrow$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 little insight to counterfactual outcomes if, e.g., the policy thresholds were set

[22] For example, years of low precipitation may be correlated with years of particularly high temperatures and, consequently, years of higher peak electricity demand. One goal of deregulated electricity markets such as CAISO is to dispatch generating units in order of marginal cost, creating a monotonically upward-sloping supply curve. Thus, by construction, years of high demand will satisfy demand with a larger portion of inefficient fossil fuel generation.

[23] For example, Eyer and Wichman [2016] show water scarcity, which varies systematically with the WYI, leads to increased demand for fossil fuel generation.

to different levels of the WYI.[24] Additionally, as I never observe outcomes in a state without regulation, I cannot compute the full effects of regulation (compared to an unregulated state) without additional structural assumptions.

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5 Results

This section presents estimates of the effects of minimum flow policies on electricity generation using the RDD framework described in Section 4.1. Prior to those estimates, I will demonstrate a few results which reinforce the applicability of the RDD research design for causal identification in this context.

5.1 Minimum flow policies are binding

Using variation in output from dams induced by changes in the minimum flow requirements is only useful if the minimum flow requirements are actually binding on dam output. I test whether stream flow 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:

$$\bar{F}_{eis} = \sum_{w \in W} \sum_{s \in S} \beta_{ws} + f_i \left(WYI_{i,e}, WYI_{i,e+1} \right) \tag{3}$$

Where $f_i(\cdot, \cdot)$ is a unit-specific flexible polynomial of the continuous WYI forecast that determines the WYT both the old and new policy regimes. Figure 4 plots the β coefficients for increases, no changes, and decreases in WYT. Approximately five 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.

5.2 Regression Discontinuity Design Estimates

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 4.1.[25] There is little density in the vicinity of the threshold between "Above Average" and "Wet" WYT categories and I am generally unable to estimate treatment effects in the vicinity of this policy

[24] 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.

[25] I compute RDD estimates and perform robust inference following Calonico et al. [2016b] using Stata code derived from Calonico et al. [2016a]. 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].

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.[26]

5.2.1 Impact of minimum flow policies on hydroelectric generation value

The event study in Section 5.1 shows minimum flow policies alter the discharge behavior of hydroelectric dams. If these policies cause dams to discharge water at times when the value of the electricity generated is low, one would expect more stringent minimum flow policies to reduce the value of electricity generated. More generally, one would expect the total value of electricity generated to be weakly lower under more stringent regulation on dam discharges holding all other factors, such as the total quantity of water available for discharge, constant.

Compared to the effects minimum flow policies on heat rates, estimation here faces a number of challenges. First, USGS and CADWR flow monitors downstream of hydroelectric dams have gaps in their reporting and I cannot impute hourly generation for some dams in some months. Second, I am unable to obtain real-time electricity prices for the NP15 region of CAISO from early 2003 through the end of 2005.[27] Consequently, these estimates have less precision in the region of the D$\rightarrow$BN policy change.

In Table 4, I compute the effect of changes in flow regimes tied to the WYT on the ratio of value of electricity generated by each hydroelectric dam to the *ex post* optimal value for discharging the same quantity of water using the RDD framework described in Section 4.1. Effects of the D$\rightarrow$BN policy are poorly estimated, but both the CD$\rightarrow$D and BN$\rightarrow$AN policies cause dams to discharge less efficiently. Each policy translation reduces the value of electricity generated by affected dams between 10% and 17% compared to the *ex post* optimal value.

5.2.2 Impact of minimum flow policies on fossil fuel generation efficiency

As described in Section 2.2, 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.

This leads to a central question – do flow regulations on hydroelectric facilities cause fossil fuel generators to operate less efficiently? One such measure of operational efficiency in fossil fuel generation is the heat rate.[28] I exploit the discrete changes in policies governing the environmental constraints on hydroelectric facilities to estimate the causal impact of those policies on the heat rates of fossil fuel generation.

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 system-wide efficiency of fossil fuel

[26] Despite the fact that the RDD running variable (the WYI) is mathematically derived from past and forecast future rainfall, one may still be concerned there is some manipulation of the running variable to induce outcomes associated with a specific side of the policy threshold. As described in the Online Appendix I am unable to reject the null hypothesis of running manipulation using tests common in the literature.

[27] CAISO was unable to supply accurate hourly electricity prices prior to April 2009 in response to my records availability request. I have compiled prices from 1998 to early 2003 and 2006 to the present from other sources.

[28] Numerous analyses of electricity markets rely on heat rates as a measure of generation efficiency, for example Fabrizio et al. [2007] and Bushnell et al. [2008].

generation in the NP15 region. These results are shown in Table 5 for a range of feasible bandwidths.[29] Moving from minimum flow policies in the "Critical Dry" WYT to the "Dry" WYT increases fuel consumed to generate one unit of electricity by 7.1% to 7.8%. Flow restrictions associated with "Above Normal" WTY increase fuel consumption between 6.4% and 10.4%. The "Below Normal" minimum flow restrictions increase fuel consumption between 2.5% and 9.0% but the effects are not significant for large bandwidths.

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. 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, including omission of covariates in the RDD estimation and alternative specifications of the local linear trends around the policy thresholds. Details of these results are provided in the Online Appendix. Further, 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 with a change to either the treatment variable or the outcomes where, if changes in minimum flow policies are driving the observed reduction in fossil fuel generation efficiency, you would expect to see a zero estimate. In particular, I the effect of instream flow policies on heat rates of fossil fuel generation in the Electric Reliability Council of Texas (ERCOT), and generally find precisely-estimated zero effects. Results are provided in the Online Appendix.

5.3 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 in 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 2.2, 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 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

[29] 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. I further restrict the maximum bandwidth to 0.9 so the data underlying the local linear regression is restricted to outcomes within a single WYT on each side of the discontinuity. When possible I have computed asymptoticly square 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.

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 4.1 to additional outcome variables related to each of these mechanisms. The estimates for the narrowest feasible bandwidth are shown in Table 6.

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 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.

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).[30] 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 5 is similar to the effect of other flow policies.

6 Implications

The estimated impacts of these policies are substantial. Table 7a breaks down the estimated annual cost in electricity generation of each set of minimum flow policies. Direct costs to hydroelectric generation range from \$23.1 to \$33.0 million per year. However, spillovers to fossil fuel generators are of comparable magnitude, ranging from \$25.4 to \$42.9 million per year. Including damages from the additional carbon emissions, between 50.1% and 70.9% of the cost of these policies are the result of spillovers into fossil fuel generation.

While the costs of these policies, in particular the spillovers into fossil fuel generation, are the primary focus of this research. It is important to frame these costs against the benefits and other costs of minimum flow policies. However, while the high resolution of policy changes and data provide a platform for detailed analysis on the impacts on electricity generation, data illuminating the potential costs and benefits are not as rich and are unsuited for the econometric methods I have deployed when estimating the impacts on electricity

[30] 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.

generation. Economic data, for example, recreation activities have at best annual resolution and may span multiple policy changes.

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.[31] Using these estimates and impacts of the each suite of flow policies on Delta outflows, I compute the marginal Environmental and Agricultural benefits of each policy. The results are shown in Table 7b. In general, total benefits exceed the estimated costs of the policy. However, spillovers to fossil fuel generation are large compared to the purported benefits, and are clearly a relevant component of policy analysis.

As an alternative, Table 7c 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.[32] Only the broad Food and Drinking Establishments and Recreation categories report annual payroll in excess of the estimated costs of these policies.[33]

The magnitude of these 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[34] range from six to seven million visitor-days per year, implying policy-related costs of nine to thirteen 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.[35]. The electricity market costs of these minimum instream flow policies comprise somewhere between 25% to 100% of the *total* value of recreation activity in the Sacramento Valley.

One should also consider how the magnitude of these spillovers may evolve over time. The spillovers from these policies are likely to only increase with time. As described in Section 5.3, 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 these costs.

[31] CALVIN (`https://calvin.ucdavis.edu/node`) is economic-engineering model of water operations in California's central valley developed by researchers at the University of California, Davis. While results from CALVIN provide an estimate of the costs of instream flow policies, it is unsatisfactory for a number of reasons. First, 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. Second, there are additional benefits of instream flow policies not accounted for in CALVIN, such as increased or more enjoyable recreation activities.

[32] There are other benefits to these policies as well that I am unable to quantify here. These include benefits of flood management, providing habitat for endangered species, and preventing salt water incursion in the Sacramento-San Joaquin Delta, California's largest source of fresh water.

[33] 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.

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

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

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 adjust output forces fossil fuel generators – with large adjustment costs – to more often alter output in response to changing demand. This is demonstrated in Figure 5, 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. Constraints on the ability 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, in this setting, variation in the stringency of minimum flow policies tied to the WYT means I observe individual plants exposed to the range of policies on multiple occasions. This variation allows me to use individual plants as their own controls, credibly estimating both the direct effect of policy changes and spillovers to unregulated firms. This credible estimate of direct costs to hydroelectric facilities would be impossible without the imputed hourly operations data described in Section 3.2. Further, the large estimated spillovers from these policies underscore the importance of selecting credible control units when evaluating the costs and benefits of regulation. One could consider an alternative identification strategy, where regulated fossil fuel generators were used as control observations for the regulated hydroelectric dams. Such a differences-in-differences estimate would not only fail to account for the full direct cost of regulation to hydroelectric facilities but, by ignoring spillovers to firms in the same output market, would understate the true social cost of the regulations by at least 100%.

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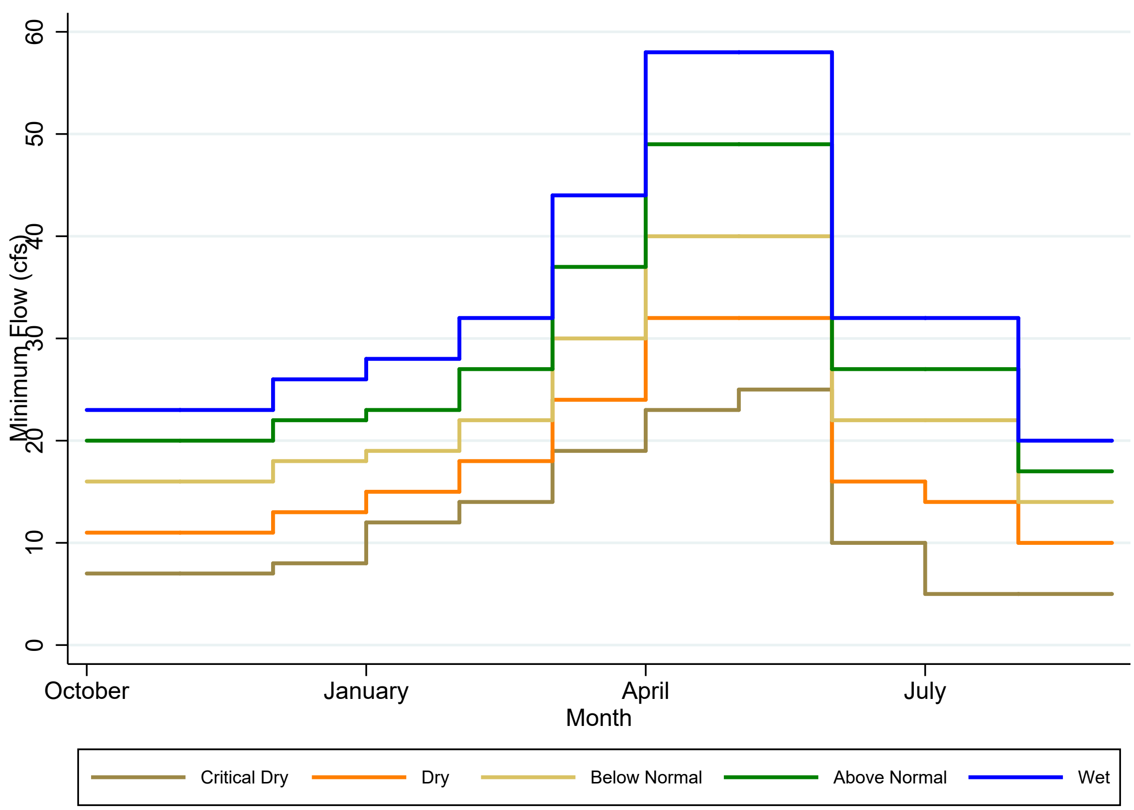
(a) Example minimum streamflow regulations

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.

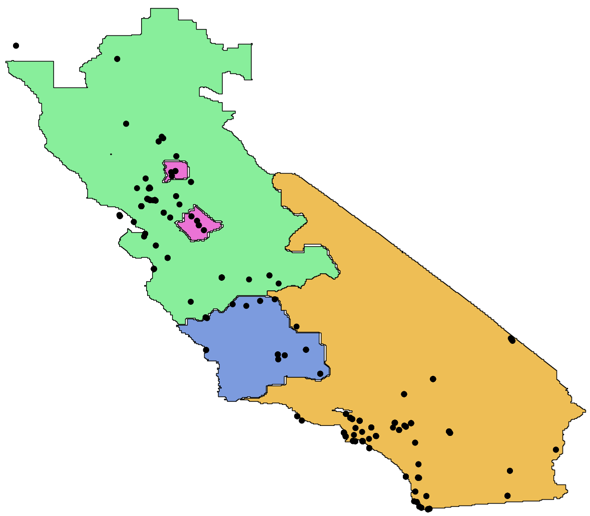
(b) Minimum flow on Gerle Creek below Loon Lake Reservoir by WYT



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.

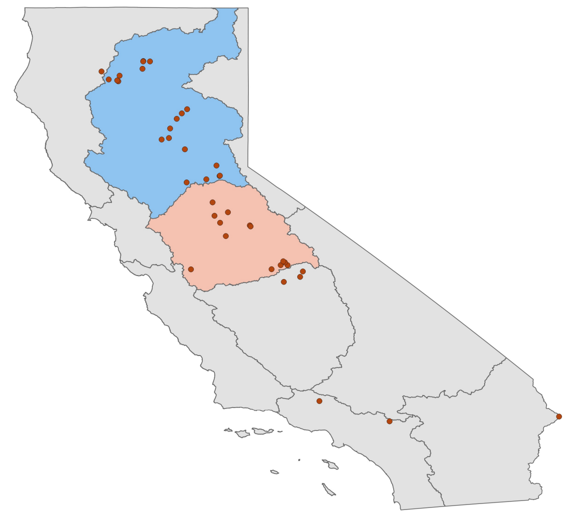
Figure 2: Map of California Electricity Generating Regions, Drainage Basins, and Electricity Generating Plants

(a) Fossil fuel generators and electricity generating regions



Map of California fossil fuel generating units reporting in CEMS and electricity generating regions. The NP15 region includes the green and pink regions.

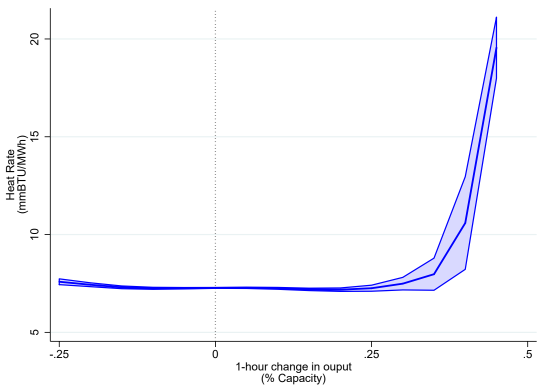
(b) Hydroelectric generators and drainage basins



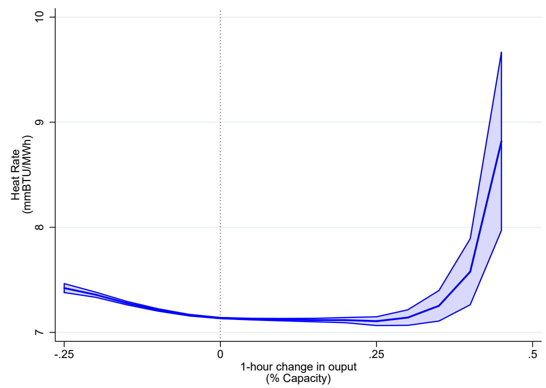
Map of large ($\geq$ 100 MW nameplate capacity) hydroelectric dams and CADWR drainage basins. The blue region is the Sacramento Valley and the pink region is the San Joaquin Valley.

Figure 3: Heat Rate Profiles for Typical Combined Cycle Gas Turbines

(a) Colusa Generating Station, Unit CT2

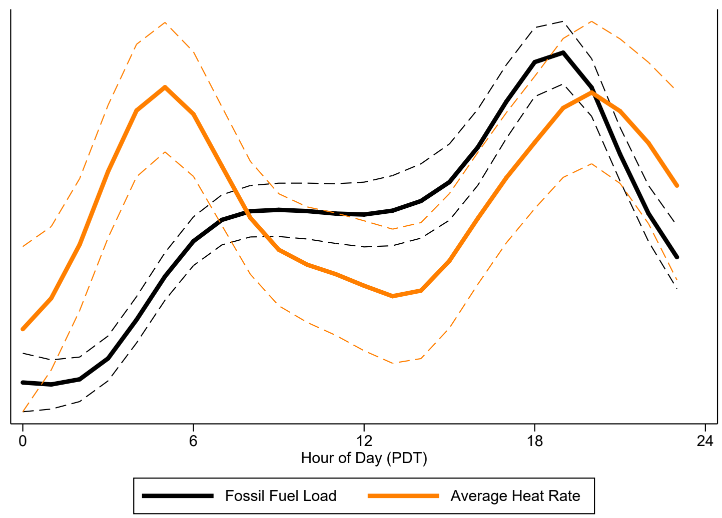


(b) Gateway Generating Station, Unit GT1



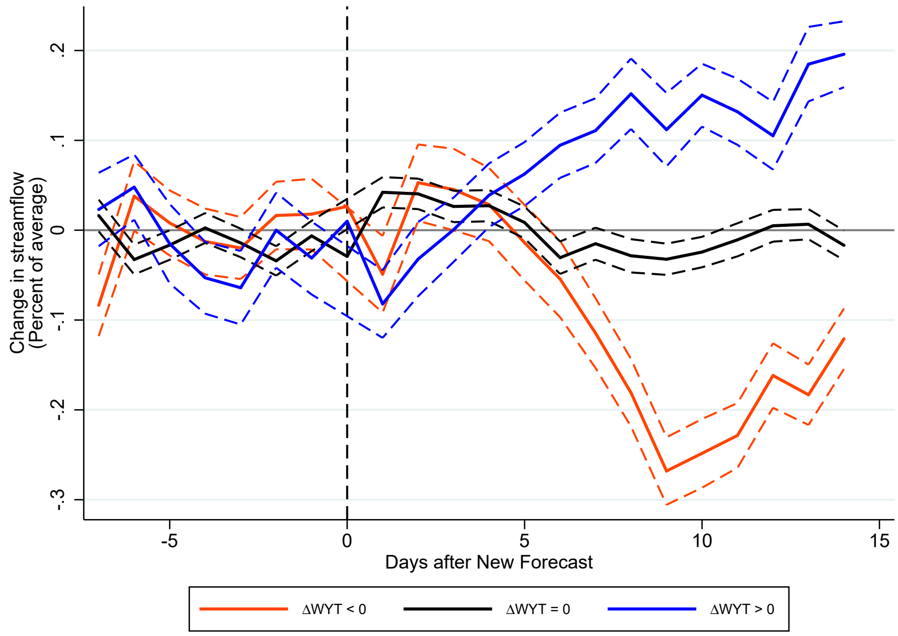
Local polynomial regression of generator heat rate as a function of the change in output during the previous hour for two CCGTs in CAISO's NP15 region. Based on operational data from CEMS from January 2012 to December 2015. Estimated as 1st-degree polynomials using the Epanechnikov kernel and data-driven 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.

(c) Fossil fuel load and average heat rate in California, May 2015



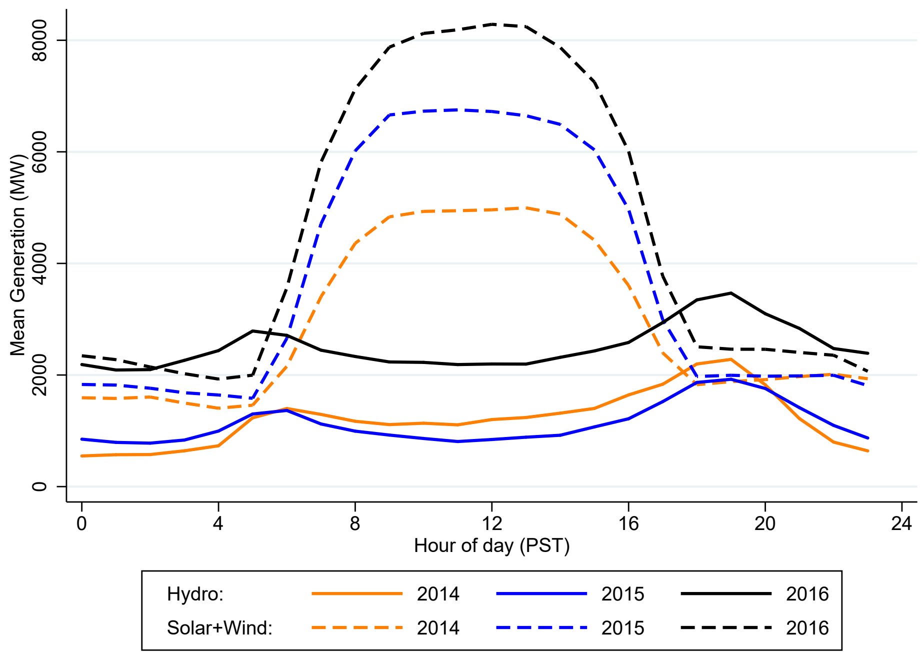
Total fossil fuel load for California from CAISO's Daily Renewables Watch shown in black. Heat rates for all fossil fuel generation in CAISO from CEMS shown in blue. Solid lines are kernel regressions of hourly observations using the Epanechnikov kernel and default data-driven bandwidths. Data limited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

Figure 4: 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 5: 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 Water Year Index is computed as a weighted average of past and forecast future stream flows through the Sacramento River system as described in Equation 1. Since 1990, values have ranged from 4.0 to 13.4.

Table 2: 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 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

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 hydroelectric generation value

(a) Policy threshold CD→D

Bandwidth	0.4	0.5	0.6	0.7	0.8	0.9
LATE	-0.150	-0.150	-0.161	-0.167	-0.145	-0.093
	(0.049)***	(0.047)***	(0.048)***	(0.050)***	(0.053)***	(0.061)
Obs. Left	47	47	47	47	54	67
Obs. Right	114	124	161	168	193	272

(b) Policy threshold D→BN

Bandwidth	0.4	0.5	0.6	0.7	0.8	0.9
LATE	-0.106	-0.079	-0.011	0.014	0.007	-0.023
	(0.057)*	(0.070)	(0.067)	(0.065)	(0.057)	(0.039)
Obs. Left	189	196	233	243	303	330
Obs. Right	92	92	111	111	117	176

(c) Policy threshold BN→AN

Bandwidth	0.9
LATE	-0.180
	(0.018)***
Obs. Left	109
Obs. Right	26

Each panel shows the change in ratio of realized value to the *ex post* optimal value of electricity generated 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 5: Effect of minimum flow policies on heat rate deviations

(a) Policy threshold CD→D

Bandwidth	0.4	0.5	0.6	0.7	0.8	0.9
LATE	0.071	0.074	0.076	0.073	0.078	0.078
	(0.007)***	(0.009)***	(0.009)***	(0.011)***	(0.015)***	(0.017)***
Obs. Left	28	28	28	28	35	42
Obs. Right	63	70	91	98	112	154

(b) Policy threshold D→BN

Bandwidth	0.4	0.5	0.6	0.7	0.8	0.9
LATE	0.090	0.080	0.062	0.051	0.032	0.025
	(0.019)***	(0.019)***	(0.016)***	(0.017)***	(0.018)*	(0.016)
Obs. Left	98	105	126	133	168	182
Obs. Right	49	49	63	63	70	98

(c) Policy threshold BN→AN

Bandwidth	0.4	0.5	0.6	0.7	0.8	0.9
LATE	0.104	0.068	0.064	0.070	0.076	0.076
	(0.013)***	(0.017)***	(0.017)***	(0.018)***	(0.021)***	(0.023)***
Obs. Left	28	56	63	63	77	77
Obs. Right	35	35	35	49	49	49

Each panel shows the change in mean heat rate local to the change in flow policy from the from the specified policy change. RDD estimates conditional on day of week fixed effects, month of year fixed effects, and a linear control for fossil fuel generation utilization. Standard errors clustered at the forecast month level shown in parentheses. *,**,*** denote results significant at the 10%, 5%, and 1% levels, respectively.

Table 6: 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.

Table 7: Costs and Benefits of instream flow policies

(a) Social cost of minimum flow policies in electricity generation

	Hydro Generation		Fossil Fuel Generation		Total
Policy	Avg. Annual Revenue ($M)	Lost Revenue ($M)	Additional Fuel Cost ($M)	Additional CO_2 Cost ($M)	Policy Social Cost ($M)
CD→D	176.95	23.18	31.49	9.18	63.86
D→BN	214.78	22.77	42.90	12.47	78.14
BN→AN	183.29	32.99	25.41	7.44	65.84

Estimated costs related to electricity generation of transitioning between minimum flow policies for the specified WYT designations in $/year. Revenues and fuel costs computed using WYT-specific averages from 2006 to 2016 and reported in 2015 dollars using the CPI, all items, seasonally adjusted. Fuel costs computed using month-specific 2015 fuel prices. Value of CO_2 additional damages is the 2015 social cost of carbon of $38/ton from IAWG [2013].

(b) 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 costs of instream flow policies derived from the CALVIN model. Benefits expressed in millions of dollars per year using 2015 dollars.

(c) 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.