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

Job Market Paper

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Draft Date: November 2, 2017

Please review and cite to the most recent version of this paper available at:
http://econjim.com/WP1701

*I would like to thank my PhD advisors David Rapson, Jim Bushnell, Erich Muehlegger for invaluable feedback on this work. David Byrne, Steve Cicala, Rebecca Davis, Lester Lusher, Erin Mansur and seminar participants at UC Davis, AERE Summer Conference, UC Berkley Energy Institute Energy Camp, the Davis Energy Economics Program (DEEP), and the University of Hawai’i at Mānoa provided useful comments. I am grateful to the UC Davis Office of Graduate Studies, College of Letters and Science: Division of Social Sciences, and the UC Davis Department of Economics for financial support. Any errors are my own.

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Abstract
Full accounting of costs and benefits are essential to policy analysis, but many regulations may have effects beyond firms directly constrained by regulation. Using a set of regulations on allowed stream flows below hydroelectric dams, this paper estimates both the direct costs of regulations to dam owners and spillovers to other firms participating in the same output market. Combining a novel method of imputing hour-to-hour operations at hydroelectric dams and previously unidentified policy variation in a regression discontinuity design, I find large effects from regulation, increasing the total costs of electricity generation as much as 19.8% and leading to millions of dollars per year in additional pollution externalities. Ignoring spillovers would substantially underestimate true policy costs, leading to suboptimal policy. Variation in these policies are analogous to an experiment manipulating the quantity of available electricity storage. My estimates show the social value electricity storage capacity is at most 72% of the capital cost of the best-available technology. Decomposition of the channels through which policy effects spill over reveal the cost of these policies will continue to grow as climate change exacerbates water scarcity and the deployment of renewable generation technologies increases.

*JEL: L51, Q25, Q51, Q52, Q53*

*Keywords: Regulation, Spillovers, Electricity, Environment*
1 Introduction

Evaluating the true costs of regulation is a central question in public policy. Regulations generally have the goal of providing some social good by constraining firm behavior away from decisions which are detrimental to provision of the beneficial good. By the very nature of altering firm behavior, such policies can reduce firm efficiency by forcing deviations from the efficient allocation of inputs or production of outputs. An optimal policy balances the marginal benefits of the social good against the marginal costs of complying with the regulation. Economists evaluating a policy typically focus on estimating its effect on production costs, efficiency, and output of firms bound by the regulation.

Firms required to comply with such regulation rarely operate in isolation. Interactions with other firms through shared input and output markets can cause regulation-induced inefficiencies to spill over to other entities whose decisions are not directly affected by the policy. Examples of such connections across firms abound; employment and environmental regulations, for example, often apply to only a subset of firms participating in a single output market. A full assessment of policy costs requires measuring both the direct costs and spillovers to other firms. This paper explores both these effects from regulation. Using novel policy variation, I compute plant-level direct costs from a suite of environmental regulations and spillover effects from those same regulations to individual, unregulated producers.

My research setting examines the impact of regulations governing the operation of hydroelectric dams on the costs of wholesale electricity supply. Wholesale electricity markets provide a good platform for observing spillovers of a policy-relevant magnitude. Inelastic supply and demand in these markets mean small deviations from the first-best can have large impacts on costs, revenues, and welfare. Further, electricity generation is characterized by a broad set of production technologies, each differing in the nature of regulations under which they are governed but producing perfectly substitutable output. These features make it likely distortions in the decisions of one firm will be communicated to the output decisions of rival firms.

I demonstrate this mechanism for spillovers by presenting a simple model of a competitive electricity generating sector. This model shows how constraints on the behavior of hydroelectric generators are communicated through the output market and increase the total costs of fossil fuel generators. It makes clear predictions on the market conditions, namely the timing and degree of inelastic fossil fuel supply, which contribute to the total cost of restrictions on hydroelectric generation. There are general implications from this model beyond wholesale electricity markets. When regulated firms are forced to reallocate output across time or space, rivals producing substitutes with convex costs will face increased total costs as a result of spillovers.

Following the predictions of this model, I estimate the impact of regulatory constraints on hydroelectric generation using high-frequency data on operations at both fossil fuel and hydroelectric facilities. Operations data for hydroelectric dams were not previously available. I develop and implement a methodological framework which combines data from stream flow monitors and
other data on hydroelectric operations to reliably impute hourly electricity generation decisions of hydroelectric dams.

Using these rich data, my goal is to estimate both direct and spillover costs of regulations on hydroelectric dams. The electricity sector model described above also highlights the challenges to causal identification of these regulations on electricity market outcomes. Mechanical correlations between total rainfall and the stringency of policies governing the dams confound simple estimates of the cost of these policies and could lead to large underestimates of the true policy cost. I combine unique policy variation and a regression discontinuity design (RDD) to address these challenges and obtain estimates of the causal effects of regulation.

Empirical results from the RDD allow me to compute the magnitude of the costs and spillovers to firms. I first establish that more stringent regulations reduce the revenues hydroelectric dams earn from electricity generation between 6.0% and 7.2%, as they are constrained away from the profit-maximizing allocation of generation through time. These regulations also lead to an allocative inefficiency, where high-cost fossil fuel generators are called upon more often due to the inability of hydroelectric generators to offer additional supply in periods of high demand. This misallocation of hydroelectric and fossil fuel output increases total system costs as much as 10.4%.

Further, effects of these policies spillover to the operations of fossil fuel generators, who are not directly constrained by streamflow regulations. More stringent policies increase plant-level fuel consumption between 4.6% and 16.4% per unit of electricity generated. As fossil fuel generation accounts for a larger portion of the market, between 50% and 80% of the social costs of the regulations are a result of spillovers.

These spillovers have salient environmental consequences. Allocative inefficiencies cause more frequent reliance on inefficient fossil fuel generators with high emissions, and productive inefficiencies mechanically increase plant-level greenhouse gas (GHG) emissions from fossil fuel generation. Regulations also result in an increase in nitrogen oxides (NO\(_X\)) emissions, particularly in areas of high population density, where pollution has the highest marginal social cost. All told, inefficiencies resulting from these regulations impose social costs between $18.7 and $126.5 million per year in effect, or about 1.5% of the total annual cost of generating electricity. These costs are similar in magnitude to estimates of other non-electricity market costs and the recreation-related benefits of these policies.

The changes in dam behavior induced by these policies approximate an experiment where electricity storage capacity, e.g., compressed air or batteries, is added to or removed from the grid. Using the same empirical framework, I estimate the change in the implied quantity of electricity storage provided by hydroelectric dams from each policy. Combined with the estimated social costs of these policies, I find the present value social benefits of electricity storage capacity are at most 66% of the capital cost of the best-available storage technology.

My results have critical implications for both water and electricity policy. Policy evaluation which ignores spillovers to the fossil fuel sector are unlikely to correctly balance benefits and
costs when determining the stringency of the policy. Additionally, I extend upon research such as Verdolini et al. [2016] and demonstrate the mechanisms through which intermittent renewable and hydroelectric generation assets are complements for cost-minimization. Large deployments of intermittent (e.g., renewables such as wind or solar photovoltaics) or inflexible (e.g., coal or nuclear) generation technologies can exacerbate the spillover effects, increasing the costs of renewable portfolio standards or other generation technology mandates. Both my theoretical framework and empirical results demonstrate that researchers must carefully consider spillover effects in policy analysis.

This paper makes a number of contributions. I exploit previously unidentified policy variation which results in repeated, discontinuous changes in the stringency of regulation to estimate the impacts of a set of environmental policies on firm productivity using a regression discontinuity design. Failing to consider the correlation between the costs of regulation and other effects driving the changes in stringency, may understate the true policy costs.

While there is a substantial literature estimating the direct costs of regulation, little attention has been directed toward the impact of such policies on unregulated firms. I am able to utilize this same policy variation to estimate substantial, positively-correlated spillovers to firms participating in the same output markets but unencumbered by these regulations. The large magnitude of spillover effects shows attention should be paid to spillovers in the analysis of regulation.

Estimating these policy effects requires high-frequency data on the electricity production decisions from hydroelectric dams, which are generally not publicly available. A large literature examining the economics of electricity markets have relied on data from EPA’s Continuous Emissions Monitoring System (CEMS) dataset, which provides rich data on plant operations, but is limited to fossil fuel generating units, requiring assumptions on the behavior of hydroelectric generators to model the full electricity generation sector. I fill this gap in plant-level electricity operations data by combining high-frequency data from stream flow monitors and other data on hydroelectric operations to reliably impute hourly electricity generation decisions by hydroelectric dams.\(^1\) Understanding the dynamic behavior of hydroelectric dams is an important component in the analysis of electricity markets, and I will make these operations data and computer code for reproducing them publicly available.

Finally, this research leads to a number of conclusions important for the analysis of regulation in electricity markets. Both the theory model and empirical results demonstrate that different electricity generation technologies, while producing perfectly substitutable output, are complements in installed capacity. Increasing the deployment of intermittent renewables, as is the goal of intermittent renewables portfolio standards throughout the United States, or reducing the capacity of hydroelectric generation, as is expected under continued climate change, can lead to substantial increases in the costs from other generation technologies.

\(^1\)The methods I deploy here are similar to, but were developed independently from, Cicala [2017]. A description of the methods are provided in Section 5 with additional detail in the Appendix.
2 Literature

This paper contributes to a broad literature examining the costs of regulation in the electricity industry. A substantial vein of previous research examines changes in efficiency resulting from the transition from cost-of-service regulation to competitive markets for generation or retailing of electricity. A typical empirical strategy controls for time-varying effects common across all generators using comparable generators for whom the regulatory environment did not change as a control group using a difference-in-differences approach.

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 markets 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 difference-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. They 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.

Most analyses of the efficiency effects of regulatory reform are unable to account for the dynamic decisions faced by owners of hydroelectric generators, with two notable exceptions. Bushnell [1998] estimates a structural model of dynamic Cournot competition between firms owning both hydroelectric and thermal generation resources. Amongst his many important conclusions, he finds operators of hydroelectric generation have limited ability to exercise market power in wet months due to large minimum flow requirements. More recently Cicala [2017] estimates the impact of market reforms on the cost of electricity generation using high-frequency data on thermal and hydroelectric plant operations, finding market deregulation reduces overall fossil fuel generation costs by $3 billion per year.

Other research considers wholesale electricity market interventions beyond cost-of-service regulation. Cullen [2013] estimates the impact of wind power on the emissions from fossil fuel power plants using exogenous variation in wind output from naturally-changing wind speeds. He finds subsidies on wind-powered generation are only justified under large values of the social cost of
Cullen [2015] estimates a dynamic, repeated entry/exit model of individual generators participating in ERCOT, a wholesale electricity market in Texas. The fitted model is then used to predict the impact of greenhouse gas regulation on the short-run behavior of generators participating in the market. He finds carbon prices in the range typically considered by regulators ($20/ton) do little to alter the short-run behavior of electricity generators.

While much of the literature considering the efficiency impacts of regulation in electricity generation focuses on cost-of-service regulation, the focus of this paper is the impact of environmental regulations on costs. Previous investigations of the impact of environmental regulation on electricity market outcomes are less common. Gollop and Roberts [1983] find sulfur dioxide emissions regulations under the 1970 Clean Air Act Amendments (CAAA) reduced the rate of annual productivity growth at fossil fuel generators compared to generators unencumbered by regulations. Nelson et al. [1993] show more stringent environmental regulations placed on new plants under the CAAA reduced the rate of capital turnover, slowing the pace of efficiency improvements over time. 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.

Researchers outside the field of economics have considered the impacts of the stream flow regulations similar to those I examine in this paper. Rheinheimer et al. [2013] uses a computational model to simulate the costs of streamflow regulations in the Upper Yuba Watershed, a subset of the region I examine, with the goal of determining the level of hydroelectric generation which maximizes ecological benefits. Tanaka et al. [2011] uses a similar computational model to estimate the costs of increases in required river outflows. Both computational models account for lost revenue to hydroelectric generators but are unable to compute any spillovers to other electricity generators.

Outside of electricity generation, there are more extensive analyses of the efficiency impacts of environmental regulation. These often highlight the importance in accounting for firm-level heterogeneity; 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

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2While this model is inherently dynamic in nature, it does not consider the dynamic problem of resource allocation faced by hydroelectric dams. Nor does it need to. Less than 1% of the total electricity in ERCOT is supplied by hydroelectric dams.
regulations. Their conclusion is accounting measures of abatement costs, such as PACE, vastly overstate true abatement costs. In the research presented here, high-resolution firm-level microdata and unique policy variation allow me to control for both firm-level and time-varying unobservables.

The focus of this paper is on the relationship between policy-induced changes in the behavior of dams and outcomes in electricity markets. There is, however, a recent and growing literature that 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.

3 Model of the Electricity Market

In this paper I will estimate the impact of regulations on hydroelectric generators on outcomes in the electricity generation sector. The specific regulations place limits on the minimum level of output produced by hydroelectric dams. I describe these policies in detail in Section 4. As a prelude, it is important to understand how interactions between firms can cause these policies to spill over to unregulated firms.

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

3.1 Electricity supply

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

Hydroelectric generators have zero marginal cost, but face a “reservoir constraint” ($Q^H$) on the total quantity of hydroelectric generation ($Q^H_t$) available across the two periods. Additionally, a regulator exogenously sets hydroelectric “minimum generation constraints” which must be met in both periods ($Q^H_t \geq Q^H \forall t$). In the case that the regulator sets no minimum generation

3If electricity prices are greater than zero a dam will always choose to discharge water required by instream flow.
requirement, \( Q^H = 0 \) serves as the non-negativity constraint on hydroelectric generation.

### 3.2 Electricity demand

Demand for electricity \( (Q_t) \) is exogenous and varies each period. Consistent with the reality of wholesale electricity markets, demand is perfectly inelastic in each period.\(^4\) 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 equals the inelastic demand \( (Q_t = Q^F_t + Q^H_t \forall t) \). Since demand is perfectly inelastic, the welfare maximization problem is identical to the cost-minimization problem.

### 3.3 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. 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. I explain each of these assumptions in further detail in the Appendix. First, I require that the space of feasible hydroelectric output levels is non-degenerate. Second, the optimal level of fossil fuel generation is strictly positive in each period. Finally, total demand in the two periods are not identical.

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

\[
\mathcal{L} = -TC_0(Q^F_0) - TC_1(Q^F_1) + \sum_{t=0}^{1} \lambda_t \cdot (Q^H_t - Q^H) + \gamma \cdot \left( Q^H - \sum_{t=0}^{1} Q^H_t \right) \quad \text{(SPP.1)}
\]

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

The Lagrange multipliers \( \lambda_t \) can be interpreted as the shadow cost of the minimum hydroelectric generation constraint in period \( t \) and \( \gamma \) is the shadow value of water in the reservoir.

The first order conditions of Equation (SPP.1) lead to the following useful necessary conditions

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\(^4\)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 et al. [2002].
for cost minimization:

\[
\frac{\partial TC_0}{\partial Q^F_0} + \lambda_0 = \gamma \quad \text{(NC.1)}
\]

\[
\frac{\partial TC_1}{\partial Q^F_1} + \lambda_1 = \gamma \quad \text{(NC.2)}
\]

\[
\frac{\partial TC_0}{\partial Q^F_0} + \lambda_0 = \frac{\partial TC_1}{\partial Q^F_1} + \lambda_1 \quad \text{(NC.3)}
\]

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

### 3.4 Impact of minimum generation constraints on total costs

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

Now suppose the regulator exogenously increases the minimum flow constraint such that it binds in one period ($t = i$) and not in the other period ($t = j$).\(^5\) Then the complementary slackness condition requires $\lambda_i > 0$ and $\lambda_j = 0$ and condition (NC.3) implies

\[
\frac{\partial TC_i}{\partial Q^F_i} < \frac{\partial TC_j}{\partial Q^F_j} \quad (1)
\]

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

These results from this model highlight the intuition of how binding minimum flow constraints on hydroelectric facilities may increase total fossil fuel generation costs. An unconstrained and cost-minimizing social planner would deploy hydroelectric generation to equalize the marginal cost of fossil fuel generation over time. Introducing a binding minimum flow constraint requires deviation from this program. The constraint requires hydroelectric generation increase in the period it binds, reducing the total quantity of fossil fuel generation and, consequently, the marginal cost of fossil fuel

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\(^5\)I show in the Appendix that such a level of the constraint must exist.
generation in that period. However, the reservoir constraint requires that hydroelectric generation
must also decrease in the other time period, resulting in an increase in total generation costs.
Convexity of the fossil fuel generation cost function requires this change in fossil fuel output will
increase total costs in one period more than it decreases costs in the other.

3.5 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
$Q_H^i$ and decrease $Q_H^j$ 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 $Q_F^i$ and increase $Q_F^j$ (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:

$$PS^F = Q_F^i \cdot \frac{\partial TC}{\partial Q_F} \bigg|_{Q_F^i} + Q_F^j \cdot \frac{\partial TC}{\partial Q_F} \bigg|_{Q_F^j} - TC(Q_F^i) - TC(Q_F^j) \quad (2)$$

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

$$\frac{\partial PS^F}{\partial Q_H} = Q_F^i \cdot \frac{\partial^2 TC}{\partial (Q_F)^2} \bigg|_{Q_F^i} - Q_F^j \cdot \frac{\partial^2 TC}{\partial (Q_F)^2} \bigg|_{Q_F^j} \quad (3)$$

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 ($\varepsilon^F_i$) in each period:

$$\frac{\partial PS^F}{\partial Q_H} = \varepsilon^F_i - \varepsilon^F_j \quad (4)$$

This is a straightforward and intuitive result. In the face of an increase in the stringency 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:

\[
PS^H = Q^H_i \cdot \frac{\partial TC}{\partial Q^F} \bigg|_{Q^F_i} + Q^H_j \cdot \frac{\partial TC}{\partial Q^F} \bigg|_{Q^F_j}
\]  

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

\[
\frac{\partial PS^H}{\partial Q^H} = \frac{\partial TC}{\partial Q^F} \bigg|_{Q^F_j} - \frac{\partial TC}{\partial Q^F} \bigg|_{Q^F_i} + Q^H_j \cdot \frac{\partial^2 TC}{\partial (Q^F)^2} \bigg|_{Q^F_j} - Q^H_i \cdot \frac{\partial^2 TC}{\partial (Q^F)^2} \bigg|_{Q^F_i}
\]  

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.\(^6\) 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.

In summary, this model of the electricity generating sector makes three predictions of the effects of minimum generation constraints on hydroelectric producers. Any binding constraint will: necessarily increase the total cost of supplying electricity, increase the surplus earned by the fossil fuel sector if supply is more elastic in periods where the constraint binds, and have ambiguous impacts on the surplus earned by hydroelectric generators.

\(^6\)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.
4 Background

This paper examines the impact of environmental regulations on hydroelectric dams in the Sacramento Valley of Northern California on market outcomes for generating electricity in that same region. This is a large and important market; the total costs of supplying electricity in this region have ranged from $7.4 to $12.8 billion per year over the past decade. In this section I describe these policies governing hydroelectric dams in detail, including their motivation and specific implementation, then proceed to explain idiosyncrasies of this market which make policy spillovers likely.

4.1 Hydroelectric generation in the Sacramento Valley

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

The hydroelectric dams I consider here are each backed by a reservoir which allows the dam to accumulate water over time. These dams continuously make decisions on the quantity of water to discharge from their reservoir, through their turbines for generating electricity. Once discharged, this water flows through a waterway downstream of the dam. These features of reservoir-backed dams lead to the stylized facts embodied in the model presented in Section 3: hydroelectric dams can produce electricity at effectively zero marginal accounting cost, but face a constraint on the total quantity of electricity they can produce in a given period. Thus, each unit of discharge now carries the opportunity cost of one unit of forgone discharge at some point in the future.

4.2 Environmental regulations on hydroelectric generation

The hydroelectric dams in this region face a suite of constraints on the allowed rate of downstream river flow which vary by time of year and the expected quantity of water that will be available for discharge. These constraints have diverse goals including flood management, supporting habitat for fish and wildlife, replicating natural flow rates, maintaining water supplies, and recreation.\footnote{Specific goals for California stream flow regulations are described in California Water Resources Control Board Resolution No. 2010-0021.} Dams must follow a schedule of specified minimum rates of downstream flow which vary with the time of year and the quantity of water expected to flow through the watershed in the current year.\footnote{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.} 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 are determined by a categorical designation of the water year type (WYT). These designations are generally “Critically Dry” (CD), “Dry” (D), “Below Normal” (BN), “Above Normal” (AN), and “Wet” (W).\(^9\) The particular designation of the WYT is determined by an index of total unimpaired runoff from the drainage basin called the water year index (WYI). CADWR is responsible for issuing reports of measured runoff to date and a forecast of additional runoff through the end of October of that year.

The WYI is a weighted average of year-to-date and forecast end-of-year runoff in the drainage basin from these forecasts plus a lagged component as shown in Equation 7.\(^10\) This index is updated in each month \(m\) in which CADWR updates runoff forecasts, occurring on the first Monday of February, March, April, and May, and using actual measurements of runoff on October 1. The index includes a lagged component, the final value of the WYI from the previous water year \((\text{WYI}_{y-1})\), to approximate the quantity of water stored in reservoirs from the previous year.

\[
\text{WYI}_m = 0.4 \sum_{t=\text{Apr}}^{\text{Jul}} \text{FLOW}_t + 0.3 \sum_{t=\text{Oct}}^{\text{Mar}} \text{FLOW}_t + 0.3 \cdot \text{WYI}_{y-1} \tag{7}
\]

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

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

Additionally, while minimum flows vary throughout the course of the year, in a given month they are increasing with wetter WYT categorizations. This leads to what may initially seem like  

\(^9\)Regulations covering some dams also specify an additional water year type of “Extreme Critical Dry”. As described in Section 6 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.

\(^{10}\)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).
a counterintuitive conclusion: as the WYI moves to “wetter” categorizations, dams face more stringent constraints on their output. These features of minimum instream flow policies are readily apparent in Figure 1, which depicts the required instream flows below Loon Lake Dam graphically.

I will also note that each dam may also face additional constraints specifying a minimum number and duration of substantially increased “pulsed flows” which are likewise a function of the WYT. An example of these regulations are shown in Table 3. 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 will refer to these requirements jointly as “instream flow requirements” and the estimates I will present compute the cost of the full suite of policies for each WYT.

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

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

This systematic correlation between the expected quantity of water available for discharge and the stringency of instream flow policies leads to a challenge to identification of the policy impacts. As I describe in Section 6.1, a naive analysis could confound the benefits of relaxing the constraint on water reserves with the costs of tightening the constraint on instream flows. I address these challenges using a RDD on the discrete changes in instream flow policies at thresholds between

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11 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.

12 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.
4.3 Idiosyncrasies of electricity markets make spillovers likely

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

Wholesale demand for electricity is derived from retail demand by end consumers and is highly variable over time. The vast majority of retail consumers during the period examined here pay a rate for electricity which does not vary over the course of the month and fails to reflect scarcity in wholesale markets. This disconnection between retail demand and wholesale prices means that wholesale demand for electricity is perfectly-inelastic and those markets clear using price signals to clear exclusively by adjusting supply.

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

In such a wholesale market, one may expect to see substantial, positively-correlated spillovers from regulations on hydroelectric dams to other market participants. First, as described in Section 3, hydroelectric generators face an opportunity cost of producing electricity. A unit of generation now removes the to option to produce that unit at some other time. This reserve constraint combined with the convex costs of other generators, causes constraints on hydroelectric generation to increase the total costs of other generators.

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

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. So, from the perspective of a cost-minimizing social planner,

13The actual process of market-clearing is more complicated as it must also account for, amongst other things, constraints on the transmission network.
capacity of these 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 the Online Appendix. 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 2. 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.

In light of this, while the output of these generation technologies are perfect substitutes, from the perspective of a cost-minimizing social planner the installed capacity of hydroelectric dams, renewables, nuclear, 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 regulations place no constraints on the behavior of fossil fuel generators.

5 Data

The analyses presented in this paper combine hourly and monthly fossil fuel operations data commonly used in the literature examining electricity markets with novel data on hourly hydroelectric dam operations and the history of regulations constraining the operations of these dams. These data, including methods for imputing high-frequency operations at hydroelectric dams, are described below. Further detail and summary statistics are provided in the Online Appendix.

5.1 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 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), 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 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.\footnote{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.} 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.

5.2 Hourly operations at hydroelectric dams

Previous research using high-frequency, plant-level electricity generation data rely on the CEMS described above.\footnote{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.} 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.\footnote{This method is conceptually similar to, but developed independently from Cicala [2017]. I additionally provide unique methodological innovations to account for spillway discharges and periods where data on monthly total generation, from e.g., EIA-923, are unavailable.}

The operating licenses of most major hydroelectric dams require the dam to maintain flow through downstream waterways within specified ranges. Ensuring compliance with these instream flow constraints requires monitoring. Data from stream flow monitors are made available through the CADWR 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 is a simple function of the volume of water passing through the turbines and the distance the water falls, called the “hydraulic head” (which is a function of reservoir height). The hydraulic head is relatively stable over the course of a month, 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, reservoir elevation, and monthly discharges and net generation, I am able to impute hourly generation for all dams with downstream flow monitors.\footnote{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.}

This procedure may fail to produce a complete picture of hourly hydroelectric operations under some conditions. Dams may at times, e.g., after periods of heavy precipitation upstream,
elect to discharge more water than can flow through the powerhouse by utilizing a spillway or opening floodgates. Spillway discharges are not useful for generating electricity but are recorded by downstream flow monitors. Failing to account for spills would understate the monthly generation rate and fail to capture the true distribution of generation over time. I 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.

Additionally, there are periods where net electricity generation for hydroelectric facilities are not available on a monthly basis. This poses a challenge when computing monthly generation rates for converting hourly flows into hourly electricity generation. In these cases I rely on the physics of hydroelectricity to compute the missing generation rates. Recall, the quantity of electricity generated from discharging a given unit of water is a function of the distance the water falls and turbine efficiency. When monthly generation data are not available, I regression impute the generation rate using elevation of the reservoir surface behind the dam. Since the powerhouse elevation is constant over time, the reservoir elevation is a translation of the distance the water falls. Imputing in this manner requires only the innocuous assumption that turbine efficiency is uncorrelated with the availability of monthly discharge data.

These data fill a critical gap in data used to analyze high-frequency electricity market operations and are useful beyond this present research. I will make the imputed hourly hydroelectric operations data and computer code for replicating the imputation publicly available on my website.

5.3 Instream flow policy data

I obtain information on historical hydrological conditions from the California Department of Water Resources (CADWR) Bulletin 120. Every February, March, April, and May the CADWR releases a forecast of total unimpaired runoff in the Sacramento Valley for the current water year. Water years start with the beginning of the rainy season on October 1 and run through September 30 of the following year. These forecasts are used to compute a numeric index of total unimpaired runoff, the WYI, and a categorical designation of the level of runoff, the WYT. No comprehensive source of contemporaneous WYI measurements or WYT designation exists. I collected contemporaneous monthly forecasts of total unimpaired runoff and observed runoff from archived copies of CADWR Bulletin 120. Using information from tables in these forecasts, I compute the numeric WYI for each monthly forecast using the formula in Equation 7 and assign the corresponding WYT in effect after that forecast. I provide a full list of reconstructed WYI values and WYT designations in the Online Appendix.

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 4 compares my reconstructed value of the WYI and WYT designation to the official value in each month where data are available. In every case I correctly reconstruct the official WYT and my calculation of the WYI rounds to the official value. My reconstruction of the WYI and WYT offers two advantages over the retrospective
WYI values provided by CADWR. First, minimum flow policies are based on the WYT designation computed using the most recent value of the WYI. CADWR reports past values only for the May forecasts but I am able to compute the WYI and determine the corresponding policy regime each month forecasts are issued. Second, CADWR rounds the reported WYI to the nearest 0.1, but my calculation contains approximately four significant digits. This additional precision will be important for identification of the RDD described in Section 6.1.

6 Identification

This research focuses on determining the impact of minimum flow regulations tied to each specific WYT, a treatment $d$ on some outcome of interest $Y$. There are five distinct policies, one for each WYT, thus there are five possible treatment states, $d \in \{CD, D, BN, AN, W\}$.

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

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

This experiment is infeasible and one must rely on observational data for empirical estimates of the effect of the policy. In such an observational context, identification of a causal effect of minimum flow restrictions on electricity market outcomes faces a number of challenges, illustrated in this context by the model presented in Section 3. Social Planner’s Lagrangian from that model is repeated below in Equation SPP.1 and highlights the first challenge to causal identification addressed by this paper.

$$\mathcal{L} = -TC_0(Q_F^0) - TC_1(Q_F^1) + \sum_{t=0}^{1} \lambda_t \cdot (Q_t^H - Q_{t-1}^H) + \gamma \cdot \left( \bar{Q}_H^H - \frac{1}{T} \sum_{t=0}^{T} Q_t^H \right)$$

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

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

Identification Challenge 2. The non-linearity of the total cost function for fossil fuel generation presents a second challenge to identification. The residual quantity of fossil fuel demand is systematically correlated with the WYI. Eyer and Wichman [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.\(^{18}\) Since total costs of fossil fuel generation are convex, this implies marginal fossil fuel costs will be systematically larger in years with a low value of the WYI. Failing to account for the correlation between the WYI and residual demand for fossil fuel generation could conflate effects of the policy with impacts of water scarcity unrelated to the policy.\(^ {19}\)

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

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\(^{18}\)This fact is also implied in my model by the constraint equating demand and total supply in each period.

\(^{19}\)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.
6.1 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 1 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 difference-in-differences identification of the causal impact of minimum flow policies. A difference-in-differences estimate could control for idiosyncratic effects using the same plant at different times as a control. While 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.\textsuperscript{20} 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.

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

$$Y_{it} = \beta^{AB} \cdot d^{AB}_t + f^{AB}(WYI_t, d^{AB}_t) + \Gamma^{AB}_i + \Xi^{AB}_m + \varepsilon_{it} \quad (9)$$

Where $Y_{it}$ is the outcome of interest, $d_t$ is an indicator for treatment set to zero for observations under policy $A$ and one for observations under policy $B$. To account for the fact that outcomes may vary with the quantity of water available for discharge, $f(\cdot)$ is a flexible polynomial in the WYI, with all parameters estimated separately on each side of the discontinuity. Following the suggestion in Gelman and Imbens [2014], my preferred estimates specify $f(\cdot)$ is a local linear trend using the triangle kernel over the desired bandwidth. $\Gamma_i$ is a vector of plant-level fixed effects and $\Xi_m$ are month-of-year fixed effects. I estimate the model parameters for each policy separately; the treatment effects, polynomial trends in the WYI, and fixed effects have separate values for each potential policy change $A, B$. This idiosyncratic error term $\varepsilon_{it}$ may be correlated within plants and within months and I compute test statistics robust to arbitrary heteroskedasticity and correlation within plants and within months using the two-way clustering procedure described in Cameron and Miller [2015].

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

\textsuperscript{20}For example, Eyer and Wichman [2016] show water scarcity, which varies systematically with the WYI, leads to increased demand for fossil fuel generation.
my estimating equation excludes the cross-sectional dimension and fixed effects, becoming:

\[ Y_t = \beta^{AB} d_t^{AB} + f^{AB}(WYI_t, d_t^{AB}) + \Xi^{AB}_m + \varepsilon_t \]  

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

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

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

The RDD also provides a satisfying solution the Identification Challenge 3. Treated and control units are drawn from the same pool of observations where values of the WYI are close to a policy threshold. In this narrow range around a policy threshold, the fact that WYI for a particular observation is above (treated) or below (control) the threshold is a function of a past precipitation and future forecasts and likely uncorrelated with outcomes treatment status of other observations close to the threshold, satisfying the SUTVA assumption.\(^{21}\)

The RDD provides many attractive attributes for causal identification in this setting. These benefits come with limits to interpretation which merit discussion. As identification of the causal effect of a policy comes from outcomes with a WYI value close to the critical value of the WYI where the policy changes from one WYT to the next, the estimates are a local average treatment effect of the schedule of flow policies under one WYT compared to the next-less restrictive WYT. For example, I am able to estimate the additional impact of moving from the D policy to the BN policy, a policy change I will term D→BN, by comparing outcomes where the WYI is just above

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\(^{21}\)While the treatment/control status of an observation should not be correlated with outcomes of another observation, my empirical specifications perform inference clustering by water year to allow for any serial correlation between observations.
the policy threshold between these policies against outcomes where the WYI is just below the policy threshold. This provides a credible impact of the effect of the policy on the outcome as the policy currently exists, however, since outcomes may vary systematically with values of the WYI, these estimates offer little insight to the counterfactual outcomes if, e.g., the policy thresholds were set to different levels of the WYI. 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.

6.2 Calculation of the counterfactual benchmark

My empirical estimates are based on data spanning from 1998 to early 2017. During this period there was substantial growth in electricity demand and generating capacity, and a significant shift in the mix of technologies used for electricity generation. To account for these changes in electricity supply in a consistent manner, I compare each outcome of interest to a counterfactual benchmark. In this benchmark, I reallocate hydroelectric output, ignoring instream flow requirements, to optimize some criterion – generally minimizing total electricity generation costs. For each observation, I then compute how close the observed value of the outcome is to the benchmark.

For each set of empirical estimates, I collect hourly data for 28-day windows starting on the second Monday of each month. I then compute a counterfactual by reallocating hydroelectric generation to minimize costs given *ex post* realizations of demand and the marginal cost curve. The counterfactual reallocation satisfies constraints requiring that hydroelectric and fossil fuel output be non-negative, hydroelectric output is less than or equal to the nameplate capacity of all hydroelectric dams for which I have hourly output data, and the total quantity of hydroelectric generation over the 28-day window must equal actual hydroelectric generation.

This method of reallocating hydroelectric output in the counterfactual forms a benchmark for comparison of total costs under different realizations of instream flow policies with desirable properties. Namely, a welfare-maximizing social planner would solve a dynamic optimization problem, allocating hydroelectric output when the marginal cost of other sources are high and withholding output when marginal costs are low subject to a constraint of the total water available in the reservoir. If the social planner at some point in time chooses a level of output below the maximum, this benchmark represents an allocation of hydroelectric output that cannot be practically attained; however, it provides a consistent reference for total electricity generation costs absent instream flow constraints. This is conceptually similar to the benchmark of a fully unconstrained electrical grid in Cicala [2017].

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.

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

Clearly, this benchmark represents an allocation of hydroelectric output that cannot be practically attained; however, it provides a consistent reference for total electricity generation costs absent instream flow constraints. This is conceptually similar to the benchmark of a fully unconstrained electrical grid in Cicala [2017].

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

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

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

7 Results

This section presents estimates of the effects of minimum flow policies on electricity generation using the RDD framework described in Section 6.1. 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.

7.1 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.

As a preliminary test for manipulation, I examine whether forecasts of the WYI – which are

\footnote{This is consistent with conditions I derive from an infinite-horizon discrete time model of a cost-minimizing social planner in the Appendix.}

\footnote{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.}
manipulable – are unbiased predictors of the actual WYI measured by streamflow monitors – which is not manipulable. If rainfall 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 the Online Appendix 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 RDD literature. For each policy threshold, Table 5 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.28

## 7.2 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:

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

(11)

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 4 plots the $\beta$ coefficients for increases.

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28 I also fail to reject the null hypothesis of no running variable manipulation using the test recommended in Calonico et al. [2016b] using local polynomial approximations of the running variable density. These results are presented in the Online Appendix.
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%.

7.3 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 6.1. Looking at the histogram of WYI values in Figure 3 it is clear there is little density in the vicinity of the threshold between “Above Average” and “Wet” WYT categories. This is borne out in the RDD estimates and I am generally unable to estimate treatment effects in the vicinity of this policy threshold for any reasonable choice of bandwidth. Consequently, in the analyses that follow, I exclude this policy threshold from my analysis and instead focus on the remaining three policy thresholds.

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

The shadow cost of the reservoir constraint on hydroelectric generation is near constant in the short-run. As outlined by the model in Section 3, a cost-minimizing social planner would allocate hydroelectric generation over time so that hydroelectric output is the highest when the marginal cost of other generation sources, typically fossil fuel generation, is high and withhold hydroelectric generation when the marginal cost of other generation sources is low.

The event study in Section 7.2 shows minimum flow policies alter the discharge behavior of hydroelectric dams. One would expect binding constraints on hydroelectric generation to create an allocative inefficiency in electricity generation. Dams are forced to discharge water and generate electricity in periods when the cost of displaced generation is low, leaving less water available for discharge when the marginal cost of electricity from other sources is high.

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

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29 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].
In each month of the year, I compute the marginal fuel cost per MW of each fossil fuel generating unit operating in the CAMEX eGRID subregion, which is essentially identical to the footprint of the CAISO.\textsuperscript{30} One could then construct a supply curve by rank-ordering plants according to their marginal costs. Fossil fuel generating units, however, can be unreliable and should not contribute to the supply curve when down for maintenance or otherwise unable to produce electricity. No comprehensive source of power plant outages is available. As an alternative, I compute mean forced outage factors for plants based on the primary fuel and generation technology from the National Electricity Reliability Council’s (NERC) Generating Unit Statistical Brochure using a method similar to Borenstein et al. \cite{borenstein2002}. I then compute the supply curve as the mean of 1,000 Monte Carlo simulations of the rank-ordered supply curve where fossil fuel units are unavailable at rates determined by their forced outage factor.

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

Following the method of constructing a counterfactual described in Section 6.2, I compute a benchmark of the cost-minimizing allocation of hydroelectric generation, transferring hydroelectric output from the hours of lowest marginal fossil fuel generating cost to those of highest marginal cost.\textsuperscript{31} I assume all counterfactual changes in hydroelectric output are absorbed one-for-one by fossil fuel generators, shifting counterfactual fossil fuel demand accordingly. I compute the total cost of fossil fuel generation, both realized and counterfactual, by integrating under the supply curve up to the quantity demanded.

My calculation of the change in costs realized by optimal reallocation of hydroelectric output is illustrated in Figure 5. The upward-sloping curve represents the fossil fuel supply curve for that month, computed using the Monte Carlo simulation described above. In each panel, the line labeled “Realized” is the realized residual demand for fossil fuel generation in a given hour. Panel (a) shows an hour where total costs are reduced by increasing hydroelectric generation, offsetting the need for some high marginal cost fossil fuel generation.\textsuperscript{32} The line labeled “Optimal” shows the counterfactual demand for fossil fuel generation. The shaded area in between is the total reduction in fossil fuel generation costs achieved in this hour by optimal reallocation of hydroelectric

\textsuperscript{30}I compute the fuel cost per MW as the price of fuel purchased by the plant, from EIA-903/923, and the plant’s heat rate from CEMS. I am currently collecting plant-level variable operating and maintenance costs and plan to add these non-fuel operating costs in this calculation in the future.

\textsuperscript{31}Since generators are assumed to have constant marginal cost, there are portions of the supply curve that are flat and the solution to the cost minimization problem may not be unique. My minimization algorithm makes total cost-reducing reallocations of hydroelectric generation, subject to non-negativity and capacity constraints, until no additional reallocations can be made, finding one of potentially many cost-minimizing allocations.

\textsuperscript{32}As described in Section 6.2, I require total hydroelectric generation over the course of each 4-week period to be identical to actual generation. So the increase in hydroelectric generation in this hour, with high marginal fossil fuel cost, is made possible by corresponding decreases in some other hours with lower marginal fossil fuel costs.
Increasing hydroelectric output can reduce costs in that hour, but comes with a price: there is less water available for discharge in some other period. Panel (b) shows the same graph for a different hour where hydroelectric generation is decreased. This raises total fossil fuel generation costs in that hour by the amount in the shaded area. From these graphs it is clear how the reallocation of hydroelectric generation decreases costs. The increase in hydroelectric generation in Panel (a) is nearly identical in magnitude to the decrease in Panel (b). However, the total cost reduction in Panel (a) is much larger than the total cost increase in Panel (b). This process reallocates hydroelectric discharges, respecting non-negativity and capacity constraints, from periods of low marginal cost to periods of high marginal cost, across a 28-day window to the total cost-minimizing allocation of hydroelectric generation.

I compute the ratio of realized to optimal total fossil fuel generation costs for four-week windows starting with the second Monday in each month. I then estimate the effect of instream flow policies on this ratio using the RDD framework from Section 6.1. A scatter plot of the the ratio of realized total generation costs to the optimal benchmark in the vicinity of each policy threshold are shown in Figure 6.

It is important to note, since total costs are computed using a constant supply curve in each month, these estimates capture changes in total generating costs assuming zero adjustment costs across all fossil fuel units. If it is costly to adjust fossil fuel output, these estimates represent a lower bound on the costs of minimum instream flow policies. I present estimates in Section 7.3.3 which capture adjustment costs at the plant-level.

The estimates for a range of bandwidths are shown in Table 6. The CD→D policy has precisely-estimated zero effects on total costs. The D→BN policy leads to increased generation costs on the order of 9% to 10%. There is weak evidence on small increases in total costs from the BN→AN policy.

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

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33CADWR forecasts, and associated WYI and WYT designations are issued on the first Monday of February, March, April, and May and become binding seven days later.  
34Since my simulated supply curve is weakly increasing in load, the algorithm for the counterfactual reshuffles hydroelectric output from periods of low residual fossil fuel demand (and low marginal costs) to periods of high fossil fuel demand (and high marginal costs). This reshuffling, by construction, reduces the hour-to-hour variability in the residual demand for fossil fuel generation and would reduce adjustment costs. Accounting for adjustment costs would likely lead to additional cost-reducing reshuffling of hydroelectric output, making my counterfactual a lower bound on total cost reductions.
policy, minimum flow requirements become less binding on the decision of dams to discharge at or near capacity when fossil fuel generation costs are high.

7.3.2 Impact of minimum flow policies on hydroelectric generation revenues

The model in Section 3 demonstrates the change in hydroelectric revenues from increasing the stringency of instream flow requirements is ambiguous, both in sign and magnitude, and depends on the elasticity of fossil fuel supply and allocation of hydroelectric output.

Here I consider the impact of instream flow policies on the revenues earned by hydroelectric generators. Note that these estimates speak little to the welfare impacts of instream flow policies, but only to the incidence of the policy. Since demand for electricity is near perfectly inelastic, lost revenues by hydroelectric generators represent transfers between consumers and various generators and may have minimal impact on total surplus. The fact that offer curves at the nodal level are not available from CAISO presents an additional limitation of this analysis. Absent information on the aggregated bid curve, I am unable to compute counterfactual prices as dams adjust their output. Here I assume perfectly elastic supply by non-hydroelectric generators, so reallocation of hydroelectric generation has no effect on prices. Scatter plots of the ratio of realized hydroelectric dam revenues compared to the optimal benchmark are shown in Figure 7.

In Table 7, I compute the effect of changes in flow regimes tied to the WYT on the ratio of revenues from electricity generation by each hydroelectric dam to the \textit{ex post} optimal value for discharging the same quantity of water using the RDD framework described in Section 6.1. Effects of the D→BN policy are poorly estimated, but all policies appear to cause dams to discharge in ways that reduce profits. Revenues at affected dams are reduced between 6.6% and 7.2% compared to the \textit{ex post} optimal value.

7.3.3 Impact of minimum flow policies on fossil fuel generation efficiency

As described in Section 4.3, efficiency losses stemming from operational constraints on hydroelectric facilities may spill over into other forms of electricity generation as well. For example hydroelectric generation, due the ability to near costlessly and instantaneously adjust output, can smooth out short-term changes in the residual demand faced by fossil fuel generation, thereby reducing adjustment costs and lowering overall system costs. Regulations which reduce the ability to adjust output will diminish this damping effect and tend to raise overall system costs.

The analysis in Section 7.3.1 computes the system-wide increase in fossil fuel generation costs assuming a static supply curve from hour-to-hour. Those estimates are unable to account for changes in within-plant efficiency resulting from instream flow policies. Namely, changes in variability of residual demand may lead to additional cycling of individual fossil fuel generators and increase plant-level adjustment costs. Further, policy-induced restrictions on water availability could cause fossil fuel plants using surface water for cooling to make operation decisions which reduce their water intensity but cause them to be less efficient converting fuels into electricity.
This leads to a central question – do flow regulations on hydroelectric facilities cause individual fossil fuel generators to operate less efficiently? One such measure of operational efficiency in fossil fuel generation is the heat rate.\textsuperscript{35} Similar to the analysis of instream flow policies on total generation costs, I aggregate the mean heat rate over all fossil fuel generators for 28-day periods starting on the second Monday of each month.

The composition of the fossil fuel plants called upon in each month may vary in ways that are correlated with the total demand for electricity.\textsuperscript{36} Further, allowing between and within-plant variation would capture some of the same effects of the allocative inefficiency estimated above. To account for these facts, I aggregate the quantity-weighted mean deviations from plant-specific average heat rates as the measure of plant efficiency in this analysis.

I investigate the impact of minimum flow restrictions using the aforementioned RDD. For each WYT, I estimate impact of moving to the next-most restrictive WYT on the above measure of plant efficiency. The results are shown in Table 8 for a range of feasible bandwidths.\textsuperscript{37} Moving from minimum flow policies in the “Critical Dry” WYT to the “Dry” WYT increases fuel consumed to generate one unit of electricity by 4.6% to 5.1%. Flow restrictions associated with “Above Normal” WTY increase fuel consumption between 4.2% and 14.7%. The “Below Normal” minimum flow restrictions increase fuel consumption between 5.9% and 15.9% but the effects are not significant for large bandwidths. I depict these results graphically for a range of bandwidths in the Online Appendix.

These results are presented graphically in Figure 8. Each panel shows a Lowess-style plot of the heat rate deviations as a function of the WYI. A solid black line represents the policy discontinuity. These plots broadly demonstrate an important concern for identification in this context. While heat rates tend to decline as the WYI increases, they sharply increase when the WYI crosses a policy threshold. Empirical analyses failing to account for the general downward trend in heat rate as a function of WYI will tend to understate the impact of the policy on thermal efficiency of electricity generation.

### 7.3.4 Placebo test

As described in Section 6.1, the RDD estimates are attractive for causal identification of the impact of minimum stream flow regulations on the efficiency of electricity generation. While RDDs simulate many attributes of the gold-standard randomized control trial in the vicinity of the policy

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\textsuperscript{35}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].

\textsuperscript{36}Given an upward-sloping supply curve, one would expect inefficient plants to be called on more often in months with high demand.

\textsuperscript{37}The local linear regressions underling the RDD require two distinct values of the WYI on each side of the discontinuity, setting a lower bound on the feasible bandwidth for each policy threshold. When possible I have computed asymptotically 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.
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.

**Placebo treatment - outcomes in a disconnected market:** I replace the outcomes in my analysis, the hourly system-wide heat rate of fossil fuel electricity generation, with outcomes from a disconnected market lacking the same policies regulating the minimum flow on hydroelectric facilities. Specifically, I construct a measure of system-wide heat rates for generation in the Electric Reliability Council of Texas (ERCOT) using identical methods I use for the NP15 region of CAISO in my primary specification.\(^{38}\) One would expect the minimum flow regulations to have no effect on the efficiency of generation in disconnected markets. Figure 9 shows these results graphically. Across the range of bandwidths from my primary specification the estimated effect of Northern California’s minimum flow policies are precisely estimated, very close to zero, and generally statistically insignificant.

### 7.4 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 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.

\(^{38}\)ERCOT is an independent system operator responsible for balancing electricity supply and demand in a region covering most of the state of Texas. As of 2016 CAISO and ERCOT operate on separate electricity interconnections defined by the North American Electric Reliability Council (NERC) and no major transmission lines connect these regions. The ERCOT and NP15 region of CAISO are effectively disconnected markets. Furthermore, the EIA reports less than 0.1% of electricity generated in ERCOT in 2014 was generated by hydroelectric facilities. Even if precipitation is geographically correlated between the Sacramento Valley and Texas, availability of water for hydroelectric generation is likely not to be an issue in the ERCOT region.
Emissions of other local criteria pollutants, such as NO\textsubscript{X} or sulfur dioxide (SO\textsubscript{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\textsubscript{X} and SO\textsubscript{2} across the United States. For each fossil fuel plant, I observe hourly NO\textsubscript{X} and SO\textsubscript{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.\textsuperscript{39}

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 10 with the emissions rate (quantity of pollution per MW of electricity), average marginal damages, and total damages for each local criteria pollutant as outcomes. For brevity, details of these results are presented in the Online Appendix.

These estimates show substantial increases, between in the total damages from NO\textsubscript{X} emissions for the D→BN and BN→AN policies, with the principal driving factor being an increase in the quantity of emissions. Instream flow policies have an ambiguous effect on SO\textsubscript{2} damages. Increasing the stringency of instream flow policies tends to increase SO\textsubscript{2} emissions, but there is weak evidence emissions are reallocated to plants with lower marginal damage rates. In the end, the change in SO\textsubscript{2}-related damages from each policy are generally statistically indistinguishable from zero.

7.5 Policy total costs

The estimated impacts of these policies are substantial. Table 9 breaks down the estimated annual cost in electricity generation of each set of minimum flow policies. Inefficiencies resulting from the misallocation of hydroelectric generation over time raise the total cost of fossil fuel generation between $0.5 and $47.4 million per year. However, productive inefficiencies at fossil fuel plants resulting from instream flow policies are substantial, ranging from $13.86 to $52.58 million per year. Including damages from the additional GHG and local criteria pollutant emissions, the

\textsuperscript{39}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.
bulk of the cost of these policies are the result of spillovers into and externalities from fossil fuel generation.

7.6 Other policy costs and benefits

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

7.6.1 Other policy costs

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

In spite of these shortcomings, I use estimates from Tanaka et al. [2011] to compute estimate costs of each suite of flow policies on Delta outflows. These costs are divided into agricultural, water used to maintain instream flow rates cannot be deployed for agricultural use, and environmental, rather than discharge to the Delta, water could be used to maintain upstream riparian ecosystems. Estimates of these costs are shown in Table 10. In general, total costs to environmental and agricultural uses are of similar magnitude to the estimated costs in electricity generation.

7.6.2 Policy benefits

Instream flow policies provide many social benefits as well. Stated goals of these policies include flood management, supporting habitat for fish and wildlife, replicating natural flow rates, maintaining water supplies and support of recreation activities. Electricity market costs estimated using the RDD represent a local average treatment effect (LATE) of each instream flow policy. Obtaining a similar LATE for these benefits as a function of instream flow policies is not possible given the available data. Instead, for a frame of comparison, I have compiled data on the total consumer valuation of some of these purported benefits.

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40The CALVIN model is an economic-engineering optimization model of California water systems used to model water policy, operations, and planning problems.
Table 11 summarizes economic activity associated with the recreational benefits of these policies using total payroll in specific NAICS industries for counties in the Sacramento Valley watershed. From these results it is clear the costs, and in particular the spillovers to fossil fuel generation, of these minimum flow policies are of similar magnitude compared to the total economic activity from recreation activities. Only the broad Food and Drinking Establishments and Recreation categories report annual payroll in excess of the estimated costs of these policies.41

The magnitude of electricity market costs are also large compared to the total value consumers may place on river-related recreation in the Sacramento Valley. The California State Park System reports total annual visitors to state parks in regions adjoining the Sacramento Valley River system42 range from six to seven million visitor-days per year, implying policy-related electricity market costs of two to twenty three dollars per visitor day. The US Bureau of Reclamation reports use-related valuations of river activity ranging from $13.67 to $34.75 per visitor-day in 2015 dollars.43 The LATE of instream flow policies on electricity market costs comprise somewhere between 8% to 146% of the total value of recreation activity in the Sacramento Valley.

7.7 Value of electricity storage

The regulations I consider here reduce allocative inefficiency by forcing dams to generate electricity in periods of low social value. Since dams face a constraint on total reserves, each unit of low value generation required under instream flow policies comes at the cost of one unit of generation with high social value. Under strict instream flow policies dams will perform less intertemporal arbitrage compared to times when they are governed by less stringent policies.

There are other technologies designed to arbitrage low-cost electricity into periods of high value. Electricity storage technologies collect electricity generated in periods of low value (and low cost) and then discharge it in periods of high value. By restricting the quantity of such intertemporal arbitrage performed by hydroelectric dams, variation in instream flow requirements act identically to a policy which varies the quantity of available electricity storage.

On the technical side, reservoir-backed hydroelectric dams have many similarities to other storage technologies, such as batteries or compressed air. Each technology faces a limit on the total quantity of electricity it can store and the rate at which it can discharge stored electricity. However, in contrast to other storage technologies, hydroelectric dams perform intertemporal arbitrage costlessly. A dam withholds one unit generation in a period of low value in exchange for one unit of generation in a period of high value. Other generation technologies store electricity

41 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.

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

43 Range of valuations from Platt [2001] deflated to 2015 dollars from the date of each study using the CPI for all goods.
in periods of low value and discharge it in periods of high value. The laws of thermodynamics require this storage/discharge cycle is not perfectly efficient and the quantity of electricity stored is always larger than the quantity discharged. This physical constraint on the efficiency of storage means estimates using hydroelectric “storage” represent an upper bound on the value of a storage technology.

I use variation in instream flow requirements to estimate the value of electricity storage. This calculation has two components, the impact of instream flow requirements on the cost of electricity generation and the effect on the quantity of intertemporal arbitrage of electricity by hydroelectric dams. This requires a calculation of the change in the quantity of storage implied by each policy change.

Suppose a hydroelectric dam produces output $Q(t)$ at all time $t$ in month $m$ with measure $\mu(m)$. Let the mean level of output from the dam be

$$\bar{Q}_m = \frac{1}{\mu(m)} \int_m Q(t) dt \quad (12)$$

Since hydroelectric dams face minimal adjustment costs and have a shadow value of reserves that is approximately constant within $m$, the output of a hydroelectric dam approximates a system where some other type of electricity generator producing constant output $\bar{Q}_m$ with attached electricity storage whose output over time is $Q^S(t) = Q(t) - \bar{Q}$. Values $Q^S(t) < 0$ imply the storage of electricity and $Q^S(t) > 0$ implies the release of stored electricity.$^{44}$

In this case, the total quantity of electricity stored between times $t_1$ and $t_2$ is

$$S(t_1, t_2) = \int_{t_1}^{t_2} (Q(t) - \bar{Q}_m) dt \quad (13)$$

The total storage capacity required to replicate behavior of the dam with an associated generator producing constant output is the difference between the largest value of $S(m_0, \cdot)$ and the smallest value of $S(m_0, \cdot)$ on interval $m$. Thus the total quantity of storage implied by a hydroelectric generator producing output $Q(t)$ in month $m$ is:

$$S_m = \max_T \left\{ \int_{m_0}^{m_T} (Q(t) - \bar{Q}_m) dt \right\} - \min_U \left\{ \int_{m_0}^{m_U} (Q(t) - \bar{Q}_m) dt \right\} \quad (14)$$

I depict this process graphically in Figure 10. Panel (a) shows hourly generation by hydroe-

$^{44}$The shadow value of reserves are a function of the total quantity of water available for discharge and change very slowly. In the empirical exercise I present here, I will compare the observed behavior of hydroelectric generators to the benchmark where the dams make production decisions which minimize total electricity generation costs subject to the constraint that within-month discharges match the observed values. As I describe in Section 6.2, this counterfactual benchmark is constructed so terminal state is identical to the observed terminal state, including the shadow value of reserves. Any deviation in the shadow value of reserves in this counterfactual must be a result of the within-month reallocation of production.
lectric dams ($Q(t)$) for a period in April 2016. The horizontal line is the mean generation during this period ($\bar{Q}_m$). Generation levels below the mean imply storage of electricity, the total quantity is the area, shaded in blue. Likewise generation in excess of the mean rate implies withdrawals from storage, with the total quantity being the area shaded in orange. The running total of storage is shown as the black line in Panel (b). The quantity (in MWh) of electricity storage required to replicate this behavior is the difference between the maximum and minimum of this line.

Using the same RDD described in Section 6.1, I compute the change in electricity storage capacity by hydroelectric dams for each policy discontinuity. In each 28-day window I compare storage implied by the realized behavior of hydroelectric dams to storage under the optimal benchmark. Storage under the optimal benchmark $S^*_m$ will be larger than observed storage due to the allocative inefficiency created by instream flow constraints. I use the difference $S^*_m - S_m$ to estimate the reduction in storage caused by an increase in the stringency of instream flow constraints. The implied value of electricity storage is shown in Table 12. The implied benefit from each MWh of electricity storage is the greatest under the D→BN policy at over $16,800 per MWh.

These calculations allow me to estimate the present value of hypothetical investments in a lossless electricity storage technology. Using the observed distribution of WYI values, I compute the expected reduction in social costs for 1 MW of electricity storage the life of the investment. I assume investments last 20 years and I discount future benefits at 4%. Under these assumptions, 1 MW of lossless electricity storage would reduce the present value of social costs by $43,068. No actual electricity storage technology would store and release energy losslessly, so this figure represents an upper bound on the true social value.

Abele et al. [2011] compute the capital costs of several electricity storage technologies considered to be near technological feasibility. They find capital costs ranging from $60,000/MWh for below-ground compressed air to $980,000/MWh for advanced lead-acid batteries. None of these storage technologies would reduce present-value social costs in electricity generation. The only currently-available storage technology, pumped hydroelectric storage, has an estimated capital cost of $250,000 to $430,000/MWh for new installations.

### 7.8 Potential channels for spillovers

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

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45For clarity, Figure 10 shows this calculation over a seven-day period. My calculations of implied storage use a 28-day period.
being idle.

Second, as described in Section 4.3, there is substantial evidence increased water scarcity pushes the generation mix to fossil fuel generating units with lower cooling water requirements. In general, these units are less efficient at converting heat into electricity. Thus, the effect of water scarcity would manifest through decreased reliance on water-intense plants or plants using fresh water for cooling. While these minimum flow policies considered here do not directly affect the total quantity of surface water available, they alter decisions on the timing and rate at which water is discharged through the river system and may simulate increased water scarcity as dams are forced to meet more stringent minimum flow requirements.

I investigate the role of each potential mechanism for each of the policy changes by applying the RDD described in Section 6.1 to additional outcome variables related to each of these mechanisms. The estimates for the narrowest feasible bandwidth are shown in Table 13.

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

This is not the first evidence that load variability increases the costs of fossil fuel generators. Cullen [2013] finds increases in the variability of electricity supplied by wind power moderately decreases the thermal efficiency of electricity generators. While my results implicate load variability as a driver of the reduction in thermal efficiency, the estimated costs represent the entirety of the policy, not just the component of cost attributable to increased variability in residual fossil fuel load.

Turning to the role of water scarcity on spillovers, the CD→D policy leads to reliance on less-water intense plants, measured by the mean rate of water intake per MW of power generated (row four) and plants that use cooling systems that do not use fresh water (row five). 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 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.

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.
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 8 is similar to the effect of other flow policies.

8 Implications

The results presented in this paper lead to implications important for electricity and water policy. Regulations governing the operation of hydroelectric dams not only reduce the value of their output, but also spill over into other unregulated firms in the market for electricity generation. Due to the sheer size of the fossil fuel generating sector, these spillover costs can substantially outweigh the direct costs to hydroelectric generators. Analyses of these policies need to account for both the direct and spillover costs when determining the optimal level of regulation.

One should also consider how the magnitude of these spillovers may evolve over time. As described in Section 7.8, 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.

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 11, 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.

The results I present in this paper consider the cost of supplying electricity while holding the capital stock fixed. Recent research, including Boomhower and Davis [2017], has noted some energy efficiency investments can result in substantial capital cost savings by reducing demand for reserve electricity generation capacity. Hydroelectric generation can provide similar benefits on the supply side by allocating generation to the hours of highest demand; it reduces the need for costly and infrequently-used reserve thermal generation capacity. While I am unable to directly estimate the impact of instream flow policies on reserve capacity requirements, any policy restricting the ability of hydroelectric dams to generate at capacity in the periods of highest demand would increase total system capital costs.

9 Conclusion

Any binding regulation, by the simple fact that it constrains firms from taking actions which would maximize profits, will reduce efficiency of the regulated firms. Other firms not bound by the regulation but connected through input or output markets may optimally respond in ways which also reduce their efficiency compared to an unregulated market. Any evaluation of the costs of regulation should account for both the direct costs and spillovers to unregulated firms.

This paper shows positively-correlated spillovers from regulation not only exist, but can be substantial in magnitude. I consider a suite of regulations governing the allowed rate of discharges from hydroelectric dams and their impact on the total cost of producing electricity from both hydroelectric and fossil fuel sources. A simple model of electricity generation shows how instream flow requirements alter the profit-maximizing decisions of dams and then spill over to the decisions of fossil fuel generators through their mutual connection in the output market for electricity supply, raising total fossil fuel generation costs, compared to a world absent regulation.

Estimating the effects of instream flow policies on electricity market outcomes is empirically challenging. Policy stringency is systematically correlated with water availability and can confound estimates which do not control for the value of additional hydroelectric generating capacity in wetter years. I address this challenge to identification by taking advantage of discontinuous changes in policy stringency at changes in the WYT using a RDD. Second, estimating the impact of instream flow regulations requires observing the output decisions of hydroelectric generators at high-frequency. I impute hourly operations at hydroelectric dams using data from downstream flow monitors.

Both the direct and spillover effects are non-trivial. Total social costs range from $18.7 to
$126.5 million per year, with over 50% of total policy costs resulting from spillovers to fossil fuel generation. The mechanisms underlying spillovers vary with water scarcity. In dry years, less water is available for cooling, forcing increased generation by less-efficient but less water-intensive fossil fuel generators. In wet years, instream flow requirements become so large the supply of hydroelectric output becomes very inelastic, forcing fossil fuel plants to adjust output or start and stop more frequently, increasing fuel consumption.

Variation in the quantity of discretionary hydroelectric output caused by changes in instream flow requirements approximates an experiment which varies the quantity of available electricity storage capacity. Using a similar empirical approach, I estimate the net present social value of 1 MWh of lossless electricity storage as $43,068, less than the per-MWh capital cost of any current or soon-to-be available electricity storage technology.

These results make several important contributions to the analysis of regulation and electricity markets. Much of the previous literature examining output decisions of electricity generators relied on hourly data from the CEMS dataset, which excludes hydroelectric generators. This paper describes and implements a framework for reliably imputing high-frequency output decisions by hydroelectric dams, allowing more comprehensive analysis of strategic behavior in electricity markets.

Empirical estimates of large spillover effects emphasize that impacts on unregulated firms participating in input or output markets with regulated firms need to be considered when analyzing policy for optimal regulation. Spillover effects are likely to be largest when demand and/or supply are inelastic or reallocating output across time or space is difficult. Further, despite the fact that various electricity generation technologies produce a perfectly substitutable output, results presented here also show the complementarity between the capital stock of thermal, renewable, and hydroelectric generation. Policies which seek to increase the portion of electricity generated from a particular source, such as renewable portfolio standards, can increase the magnitude of spillovers from other environmental policies.
References


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

Histogram of WYI for the Sacramento Valley reconstructed from each Bulletin 120 forecast from the California Department of Water Resources. Forecasts are released on the first Monday of each February, March, April, and May. Thresholds for each WYT are vertical black lines.
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: Example change in fossil fuel generation costs from hydroelectric reallocation

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

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

The graph illustrates computing the change in total fossil fuel generating costs resulting in a reallocation of hydroelectric generation at the specified time. The upward-sloping curve is the marginal cost of fossil fuel generation over the range of potential levels of residual fossil fuel demand, computed using methods similar to Borenstein, Bushnell, and Wolak [2002]. The right vertical line is the observed residual fossil fuel demand. The left vertical line is counterfactual residual fossil fuel demand where hydroelectric output is reallocated over time to minimize total fossil fuel generation costs. The shaded area between observed and counterfactual demand and under the marginal cost curve represents the change in total fossil fuel generation costs resulting reallocations in this hour. Panel (a) represents a reallocation which increases hydroelectric generation and decreases marginal cost in that hour. Panel (b) decreases hydroelectric generation and increases marginal cost.
Figure 6: Regression discontinuity total generation cost optimality

(a) Policy threshold CD→D

(b) Policy threshold D→BN

(c) Policy threshold BN→AN

Scatter plot of total generation cost optimality as a function of WYI. Scatter observations collapsed to approximately 15 observations on each side of the threshold. Lowess trends with 95% confidence intervals for each side of the discontinuity shown as the shaded region and line. Policy discontinuity shown as the vertical line.
Figure 7: Regression discontinuity hydroelectric generation revenues

(a) Policy threshold CD→D

(b) Policy threshold D→BN

(c) Policy threshold BN→AN

Scatter plot of hydroelectric generation revenues as a function of WYI. Scatter observations collapsed to approximately 15 observations on each side of the threshold. Lowess trends with 95% confidence intervals for each side of the discontinuity shown as the shaded region and line. Policy discontinuity shown as the vertical line.
Figure 8: Regression discontinuity plot of heat rate deviations

(a) Policy threshold CD→D

(b) Policy threshold D→BN

(c) Policy threshold BN→AN

Scatter plot of mean hourly deviations from average heat rates as a function of WYI. Scatter observations collapsed to approximately 15 observations on each side of the threshold. Lowess trends with 95% confidence intervals for each side of the discontinuity shown as the shaded region and line. Policy discontinuity shown as the vertical line.
Placebo sample of natural gas-fired power plants in ERCOT during the same period and using the same running variable and policy thresholds as the primary specification. Estimated effect size by RDD bandwidth. Pointwise 95% confidence intervals shown as dashed lines.
These graphs depict the calculation of the quantity of electricity storage implied by hydroelectric dam behavior. Panel (a) shows total hydroelectric generation for a week in April 2016. The horizontal line represents mean generation. Generation rates below the mean imply storage of electricity, and withdrawals when the generation rate exceeds the mean. The running total of implied storage is shown as shaded areas.

Panel (b) shows the running total of implied storage.
Figure 11: 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

<table>
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<th>Sacramento Valley Water Year Hydrologic Classifications are:</th>
<th>Water Year Index</th>
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</thead>
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<tr>
<td>Wet</td>
<td>Equal to or greater than 9.2</td>
</tr>
<tr>
<td>Above Normal</td>
<td>Greater than 7.8, and less than 9.2</td>
</tr>
<tr>
<td>Below Normal</td>
<td>Greater than 6.5, and equal to or less than 7.8</td>
</tr>
<tr>
<td>Dry</td>
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</tr>
<tr>
<td>Critical</td>
<td>Equal to or less than 5.4</td>
</tr>
</tbody>
</table>

Source: California Department of Water Resources, 2009, *CA Water Plan Update 2009*, Vol. 4 Reference Guide. The WYI is computed as a weighted average of past and forecast future stream flows through the Sacramento River system as described in Equation 7. Since 1990, values have ranged from 4.0 to 13.4.
Table 2: Example minimum streamflow regulations

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<th>AN</th>
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<td>17</td>
<td>20</td>
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</table>

Source: Upper American River Hydroelectric Project Minimum Flows. Minimum instream flows below Loon Lake Reservoir Dam as specified in the dam’s operation license from FERC.
Table 3: Minimum recreational flows at Chili Bar Dam

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<th>Wednesday</th>
<th>Thursday</th>
<th>Friday</th>
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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 4: Comparison of official and reconstructed WYI and WYT

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<td>WYI</td>
<td>WYT</td>
</tr>
<tr>
<td>1995</td>
<td>May</td>
<td>12.397</td>
<td>W</td>
</tr>
<tr>
<td>1996</td>
<td>May</td>
<td>9.708</td>
<td>W</td>
</tr>
<tr>
<td>1997</td>
<td>May</td>
<td>11.005</td>
<td>W</td>
</tr>
<tr>
<td>1998</td>
<td>May</td>
<td>12.361</td>
<td>W</td>
</tr>
<tr>
<td>1999</td>
<td>May</td>
<td>10.044</td>
<td>W</td>
</tr>
<tr>
<td>2000</td>
<td>May</td>
<td>9.229</td>
<td>W</td>
</tr>
<tr>
<td>2001</td>
<td>May</td>
<td>5.871</td>
<td>D</td>
</tr>
<tr>
<td>2002</td>
<td>May</td>
<td>6.503</td>
<td>D</td>
</tr>
<tr>
<td>2003</td>
<td>May</td>
<td>8.036</td>
<td>AN</td>
</tr>
<tr>
<td>2004</td>
<td>May</td>
<td>7.681</td>
<td>BN</td>
</tr>
<tr>
<td>2005</td>
<td>May</td>
<td>7.395</td>
<td>BN</td>
</tr>
<tr>
<td>2006</td>
<td>May</td>
<td>13.023</td>
<td>W</td>
</tr>
<tr>
<td>2007</td>
<td>May</td>
<td>6.199</td>
<td>D</td>
</tr>
<tr>
<td>2008</td>
<td>May</td>
<td>5.396</td>
<td>C</td>
</tr>
<tr>
<td>2009</td>
<td>May</td>
<td>5.489</td>
<td>D</td>
</tr>
<tr>
<td>2010</td>
<td>May</td>
<td>6.881</td>
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<td>2011</td>
<td>May</td>
<td>10.022</td>
<td>W</td>
</tr>
<tr>
<td>2012</td>
<td>May</td>
<td>6.861</td>
<td>BN</td>
</tr>
<tr>
<td>2013</td>
<td>May</td>
<td>5.790</td>
<td>D</td>
</tr>
<tr>
<td>2014</td>
<td>May</td>
<td>4.019</td>
<td>C</td>
</tr>
<tr>
<td>2015</td>
<td>May</td>
<td>3.965</td>
<td>C</td>
</tr>
<tr>
<td>2016</td>
<td>May</td>
<td>7.115</td>
<td>BN</td>
</tr>
</tbody>
</table>

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 5: Test of running variable manipulation (McCrary)

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

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

(a) Policy threshold CD→D

<table>
<thead>
<tr>
<th>Bandwidth</th>
<th>0.40</th>
<th>0.45</th>
<th>0.50</th>
<th>0.55</th>
<th>0.60</th>
<th>0.65</th>
</tr>
</thead>
<tbody>
<tr>
<td>LATE</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Obs. Left</td>
<td>11</td>
<td>11</td>
<td>11</td>
<td>11</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>Obs. Right</td>
<td>26</td>
<td>31</td>
<td>31</td>
<td>33</td>
<td>34</td>
<td>34</td>
</tr>
</tbody>
</table>

(b) Policy threshold D→BN

<table>
<thead>
<tr>
<th>Bandwidth</th>
<th>0.40</th>
<th>0.45</th>
<th>0.50</th>
<th>0.55</th>
<th>0.60</th>
<th>0.65</th>
</tr>
</thead>
<tbody>
<tr>
<td>LATE</td>
<td>0.104</td>
<td>0.100</td>
<td>0.098</td>
<td>0.078</td>
<td>0.048</td>
<td>0.036</td>
</tr>
<tr>
<td></td>
<td>(0.051)**</td>
<td>(0.052)*</td>
<td>(0.052)*</td>
<td>(0.046)*</td>
<td>(0.033)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Obs. Left</td>
<td>29</td>
<td>30</td>
<td>30</td>
<td>31</td>
<td>33</td>
<td>33</td>
</tr>
<tr>
<td>Obs. Right</td>
<td>19</td>
<td>19</td>
<td>19</td>
<td>23</td>
<td>28</td>
<td>29</td>
</tr>
</tbody>
</table>

(c) Policy threshold BN→AN

<table>
<thead>
<tr>
<th>Bandwidth</th>
<th>0.40</th>
<th>0.45</th>
<th>0.50</th>
<th>0.55</th>
<th>0.60</th>
<th>0.65</th>
</tr>
</thead>
<tbody>
<tr>
<td>LATE</td>
<td>0.008</td>
<td>0.008</td>
<td>0.018</td>
<td>0.019</td>
<td>0.019</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.010)</td>
<td>(0.010)*</td>
<td>(0.010)*</td>
<td>(0.010)*</td>
<td>(0.010)*</td>
</tr>
<tr>
<td>Obs. Left</td>
<td>12</td>
<td>14</td>
<td>20</td>
<td>20</td>
<td>21</td>
<td>21</td>
</tr>
<tr>
<td>Obs. Right</td>
<td>13</td>
<td>13</td>
<td>13</td>
<td>13</td>
<td>13</td>
<td>17</td>
</tr>
</tbody>
</table>

Each panel shows the change in ratio of realized fossil fuel generation costs to the *ex post* optimal generation costs resulting from the specified policy change estimated using the RDD described in Section 6.1 conditional on month-of-year fixed effects. Each observation is a 28-day period starting on the second Monday of the month. Standard errors clustered by the CADWR WYI designation period, updated in February, March, April, May, and October, are shown in parentheses. *,**,*** denote results significant at the 10%, 5%, and 1% levels, respectively.
Table 7: Effect of minimum flow policies on hydroelectric generation value

(a) Policy threshold CD→D

<table>
<thead>
<tr>
<th>Bandwidth</th>
<th>0.40</th>
<th>0.45</th>
<th>0.50</th>
<th>0.55</th>
<th>0.60</th>
<th>0.65</th>
</tr>
</thead>
<tbody>
<tr>
<td>LATE</td>
<td>-0.066</td>
<td>-0.062</td>
<td>-0.059</td>
<td>-0.057</td>
<td>-0.058</td>
<td>-0.059</td>
</tr>
<tr>
<td></td>
<td>(0.033)**</td>
<td>(0.033)*</td>
<td>(0.033)*</td>
<td>(0.033)*</td>
<td>(0.033)*</td>
<td>(0.033)*</td>
</tr>
<tr>
<td>Obs. Left</td>
<td>146</td>
<td>146</td>
<td>146</td>
<td>146</td>
<td>146</td>
<td>146</td>
</tr>
<tr>
<td>Obs. Right</td>
<td>332</td>
<td>392</td>
<td>392</td>
<td>417</td>
<td>429</td>
<td>429</td>
</tr>
</tbody>
</table>

(b) Policy threshold D→BN

<table>
<thead>
<tr>
<th>Bandwidth</th>
<th>0.40</th>
<th>0.45</th>
<th>0.50</th>
<th>0.55</th>
<th>0.60</th>
<th>0.65</th>
</tr>
</thead>
<tbody>
<tr>
<td>LATE</td>
<td>-0.072</td>
<td>-0.069</td>
<td>-0.068</td>
<td>-0.012</td>
<td>0.048</td>
<td>0.065</td>
</tr>
<tr>
<td></td>
<td>(0.030)**</td>
<td>(0.030)**</td>
<td>(0.030)**</td>
<td>(0.050)</td>
<td>(0.056)</td>
<td>(0.054)</td>
</tr>
<tr>
<td>Obs. Left</td>
<td>359</td>
<td>367</td>
<td>367</td>
<td>379</td>
<td>404</td>
<td>404</td>
</tr>
<tr>
<td>Obs. Right</td>
<td>223</td>
<td>223</td>
<td>223</td>
<td>274</td>
<td>315</td>
<td>315</td>
</tr>
</tbody>
</table>

(c) Policy threshold BN→AN

<table>
<thead>
<tr>
<th>Bandwidth</th>
<th>0.45</th>
<th>0.50</th>
<th>0.55</th>
<th>0.60</th>
<th>0.65</th>
</tr>
</thead>
<tbody>
<tr>
<td>LATE</td>
<td>-0.071</td>
<td>0.026</td>
<td>0.059</td>
<td>0.074</td>
<td>0.153</td>
</tr>
<tr>
<td></td>
<td>(0.033)**</td>
<td>(0.054)</td>
<td>(0.073)</td>
<td>(0.081)</td>
<td>(0.087)*</td>
</tr>
<tr>
<td>Obs. Left</td>
<td>98</td>
<td>183</td>
<td>183</td>
<td>192</td>
<td>192</td>
</tr>
<tr>
<td>Obs. Right</td>
<td>21</td>
<td>21</td>
<td>21</td>
<td>21</td>
<td>76</td>
</tr>
</tbody>
</table>

Each panel shows the change in ratio of realized value to the \textit{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 8: Effect of instream flow requirements on plant-level heat rate deviations

(a) Policy threshold CD→D

<table>
<thead>
<tr>
<th>Bandwidth</th>
<th>0.40</th>
<th>0.45</th>
<th>0.50</th>
<th>0.55</th>
<th>0.60</th>
<th>0.65</th>
</tr>
</thead>
<tbody>
<tr>
<td>LATE</td>
<td>0.046</td>
<td>0.047</td>
<td>0.047</td>
<td>0.049</td>
<td>0.050</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
<td>(0.003)**</td>
<td>(0.003)**</td>
<td>(0.003)**</td>
<td>(0.004)**</td>
<td>(0.004)**</td>
<td>(0.004)**</td>
</tr>
<tr>
<td>Obs. Left</td>
<td>11</td>
<td>11</td>
<td>11</td>
<td>11</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>Obs. Right</td>
<td>26</td>
<td>31</td>
<td>31</td>
<td>33</td>
<td>34</td>
<td>34</td>
</tr>
</tbody>
</table>

(b) Policy threshold D→BN

<table>
<thead>
<tr>
<th>Bandwidth</th>
<th>0.40</th>
<th>0.45</th>
<th>0.50</th>
<th>0.55</th>
<th>0.60</th>
<th>0.65</th>
</tr>
</thead>
<tbody>
<tr>
<td>LATE</td>
<td>0.147</td>
<td>0.137</td>
<td>0.127</td>
<td>0.062</td>
<td>0.042</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td>(0.035)**</td>
<td>(0.035)**</td>
<td>(0.035)**</td>
<td>(0.046)</td>
<td>(0.036)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Obs. Left</td>
<td>29</td>
<td>30</td>
<td>30</td>
<td>31</td>
<td>33</td>
<td>33</td>
</tr>
<tr>
<td>Obs. Right</td>
<td>18</td>
<td>18</td>
<td>19</td>
<td>23</td>
<td>26</td>
<td>27</td>
</tr>
</tbody>
</table>

(c) Policy threshold BN→AN

<table>
<thead>
<tr>
<th>Bandwidth</th>
<th>0.40</th>
<th>0.45</th>
<th>0.50</th>
<th>0.55</th>
<th>0.60</th>
<th>0.65</th>
</tr>
</thead>
<tbody>
<tr>
<td>LATE</td>
<td>0.159</td>
<td>0.164</td>
<td>0.074</td>
<td>0.063</td>
<td>0.059</td>
<td>0.066</td>
</tr>
<tr>
<td></td>
<td>(0.070)**</td>
<td>(0.065)**</td>
<td>(0.072)</td>
<td>(0.072)</td>
<td>(0.072)</td>
<td>(0.070)</td>
</tr>
<tr>
<td>Obs. Left</td>
<td>12</td>
<td>14</td>
<td>20</td>
<td>20</td>
<td>21</td>
<td>21</td>
</tr>
<tr>
<td>Obs. Right</td>
<td>13</td>
<td>13</td>
<td>13</td>
<td>13</td>
<td>13</td>
<td>17</td>
</tr>
</tbody>
</table>

Each panel shows the system mean deviation from plant-level heat rate from the specified policy change estimated using the RDD described in Section 6.1 conditional on month-of-year fixed effects. Each observation is a 28-day period starting on the second Monday of the month. Standard errors clustered by the CADWR WYI designation period, updated in February, March, April, May, and October, are shown in parentheses. **,*** denote results significant at the 10%, 5%, and 1% levels, respectively.
Table 9: Social cost of minimum flow policies in electricity generation

<table>
<thead>
<tr>
<th>Instream Flow Policy</th>
<th>Mean Annual Allocative Productive CO\textsubscript{2} Local Criteria Externality Social Cost</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FF Cost ($M/yr)</td>
<td>Inefficiencies ($M/yr)</td>
</tr>
<tr>
<td>CD→D</td>
<td>365.20</td>
<td>0.46</td>
</tr>
<tr>
<td>D→BN</td>
<td>504.69</td>
<td>47.37</td>
</tr>
<tr>
<td>BN→AN</td>
<td>382.95</td>
<td>2.98</td>
</tr>
</tbody>
</table>

Estimated costs related to electricity generation of transitioning between minimum flow policies for the specified WYT designations in $M/year. Fossil fuel generation costs computed using WYT-specific averages from 2006 to 2016, 2015 fuel prices, and reported in 2015 dollars using the CPI, all items, seasonally adjusted. Productive inefficiencies are spillovers from instream flow policies to fossil fuel generators, described in Section 7.3.3. Value of CO\textsubscript{2} additional damages is the 2015 social cost of carbon of $38/ton from IAWG [2013]. Local criteria pollutant damages for NO\textsubscript{X} and SO\textsubscript{2} computed using county-specific marginal damages estimates from Muller [2014]. Allocative costs are direct costs resulting from the misallocation of hydroelectric generation over time, described in Section 7.3.1. Effects estimated using the smallest feasible bandwidth from RDD estimators.
Table 10: Other costs of instream flow policies

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

Estimated benefits of instream flow policies derived from the CALVIN model. Benefits expressed in millions of dollars per year using 2015 dollars. Policy-Induced outflow represent the increase in annual Delta outflows in Maf. Costs are the total cost per year of the specified policy change. Environmental costs represent forgone use of water for other environmental policy goals. Agricultural costs represent lost agricultural productivity due to forgone water use.
Table 11: Economic activity by NAICS code

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

Mean annual payroll for establishments benefiting from environmental and recreation constraints on dam discharges for counties in the Sacramento Valley. Imputed using observed number of establishments and mean payroll per establishment from County Business Patterns data from 1998 to the present. Dollar value deflated to 2015 using the annual average CPI all goods.
Table 12: Implied value of electricity storage

<table>
<thead>
<tr>
<th>Instream Flow Policy</th>
<th>Implied Storage Capacity (MWh)</th>
<th>Annual Implied Storage Value ($/MWh/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CD→D</td>
<td>41,088.9</td>
<td>456</td>
</tr>
<tr>
<td>D→BN</td>
<td>51,302.5</td>
<td>2,465</td>
</tr>
<tr>
<td>BN→AN</td>
<td>3,544.6</td>
<td>16,884</td>
</tr>
<tr>
<td><strong>Present Value</strong></td>
<td><strong>43,068</strong></td>
<td></td>
</tr>
</tbody>
</table>

The social value of electricity storage implied by each policy discontinuity. Social costs of the policy computed in Table 9. Implied quantity of storage computed using the RDD estimator described in Section 6.1 on the mean quantity of within-day storage for each policy discontinuity.
Table 13: Decomposition of spillover channels

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

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.