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Does water scarcity shift the electricity generation mix toward fossil fuels? Empirical evidence from the United States[☆]

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ABSTRACT

Water withdrawals for the energy sector are the largest use of fresh water in the United States. Using an econometric model of monthly plant-level electricity generation levels between 2001 and 2012, we estimate the effect of water scarcity on the US electricity fuel mix. We find that hydroelectric generation decreases substantially in response to drought, although this baseline generation is offset primarily by natural gas, depending on the geographic region. We provide empirical evidence that drought can increase emissions of CO_2 and local pollutants. We quantify the social costs of water scarcity to be $330,000 per month for each plant that experiences a one-standard deviation increase in water scarcity (2015 dollars), a relationship that persists under future projections of water scarcity.

Introduction

Water withdrawals by power plants are the single largest use of fresh water in the United States (Kenny et al., 2009). Because power plants require water for electricity generation, either to turn hydroelectric turbines or to cool steam (Macknick et al., 2012), increased water scarcity may induce reductions in generation from relatively water-intensive power plants toward less-water-intensive plants for a number of reasons. Most directly, decreased water availability limits generation from hydroelectric power plants (Department of Energy, 2009; Vliet et al., 2012; Ricardo and Sailor, 1998). Although the direction of correlation is well-known, the magnitude by which hydro-electric production will be curtailed is uncertain. Water management practices by reservoir managers, for example, could cause changes in hydro generation to diverge from

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those suggested by engineering models alone. Other less direct mechanisms include changes in thermal efficiency associated with higher river temperatures (Linnerud et al., 2011) and higher marginal costs associated with curtailing water use (Maulbetsch and Michael, 2006; McDermott and Nilsen, 2014). Additionally, water needs vary among power plants based on fuel type and characteristics such as cooling technologies and pollution abatement technologies (Newmark et al., 2010; Meldrum et al., 2013; Feeley III et al., 2008; Averyt et al., 2011). As a result, the prevailing mix of fuel sources, cooling technologies, and water sources used for electricity generation may be impacted by changes in water availability, but their market and non-market impacts are not well identified.

Given that total electricity generation must remain relatively fixed due to regulated retail electricity prices, non-hydro electricity producers must increase generation but the extent to which various types of generation will be called upon to replace that generation is unclear. For example, water scarcity might decrease hydro-electricity generation, increasing the residual demand facing a coal power plant while simultaneously placing pressure on the coal power plant's ability to comply with water discharge temperature regulations. Because there is variation in emissions across generators, it is critically important to understand what type of generation will be affected by water scarcity and by how much.

Climate change poses immediate risks to supplies of fresh water for the production of electricity as drought becomes more frequent and more severe (Dai, 2011; Vliet et al., 2012; Koch and Vögele, 2009; Macknick et al., 2012; Olmstead, 2014; Schewe et al., 2014; Vörösmarty et al., 2000). Several studies estimate the effect of water supply shocks on electricity production, but this literature, generally, is limited by modeling frameworks and assumptions (Bell et al., 2014), narrow geographic focus of analyses (Yates et al., 2013; Madani and Jay, 2010; Flores-López and Yates, 2013), and restricted thematic scope (Macknick et al., 2012; Meldrum et al., 2013; Ricardo and Sailor, 1998; Scanlon et al., 2013).

There is, however, an economics literature that estimates the change in heating and cooling energy use as temperatures rise dating back to the early 1990s (Baxter and Calandri, 1992; Rosenthal et al., 1995). In recent years, this question has been asked with increasingly novel data and methods with implications for human adaptation. Deschênes and Greenstone (2011), Barreca et al. (2016), and Aroonruengsawat and Auffhammer (2011), for example, estimate energy consumption using state-level and household-level panels, respectively, to examine how consumers adapt to rising temperatures.[1] Little effort, however, has been given to examining the role of water scarcity in this capacity.

In this paper, we build upon insights from an evolving literature that econometrically estimates the effect of weather fluctuations on economic activity to predict damages from climate change (Dell et al., 2014, 2012; Burke et al., 2015; Hsiang et al., 2013; Schlenker and Michael, 2009; Barreca et al., 2016; Carleton and Solomon, 2016). Specifically, we estimate a reduced-form panel data model of plant-level electricity generation across the United States to uncover a relationship between water scarcity and electricity production. To our knowledge, this is the first representative econometric analysis of the vulnerability of the electricity sector to changes in water scarcity. We do not attempt to decompose the avenues through which drought may affect electricity systems. Instead, we acknowledge that the various causal mechanisms may be interdependent and we estimate the aggregate effect of water scarcity on the electricity mix, including associated feedbacks among the mechanisms.

We investigate the effect of variation in water scarcity on plant generation using two related econometric approaches. First, we construct a representative panel of monthly electricity generation from power plants in the United States that were in operation between 2001 and 2012, inclusive. Using a linear fixed effects panel data model and controlling for weather shocks that influence electricity demand, we explain the degree to which residual variation in generation decisions can be attributed to changes in the Palmer Drought Severity Index (PDSI), a physical water balance model, which we use as a proxy for water scarcity (Alley, 1984). While the PDSI is not directly related to electricity production, it correlates strongly with river flows and precipitation, which are in turn correlated with water temperature, limiting the thermal efficiency of power plants and triggering environmental protection regulations. It is commonly used to project the effect of climate change on water availability (Dai, 2011). Moreover, the PDSI provides a measure of water scarcity that is comparable throughout the country, abstracting away from the spatial variation in water-electricity mechanisms (e.g. storage, snow pack reliance) and allowing for a national assessment of the link between water scarcity and electricity. We also note that unlike alternative measures of water availability, such as runoff, PDSI has been projected well into the future on a relatively fine timescale.[2] Throughout our study period, we capture several severe droughts that vary spatially. During each drought, some regions experience no drought or even water abundance, which aids in identification. An important takeaway is that the PDSI level moves independently of measures of temperature. Because drought is a longer-term trend, its effect on electricity generation will be differentiated from instantaneous weather patterns and seasonal demand shocks. This fact is central to our identification strategy: conditional on seasonal trends, temperature, and other demand shocks, changes in water scarcity is a plausibly exogenous shock to electricity generation.

By exploiting data on observable characteristics of power plants, we also estimate heterogeneous effects of water availability on plant generation. Specifically, we focus on the type of water source on which the plant generally relies and the type of technology that thermal power plants use to cool generators.

Second, in order to account for water scarcity–induced changes in generation along unobservable plant dimensions, we directly estimate CO_2, NO_x, and SO_2 emissions from the electricity sector as a function of water availability. We construct a

[1] See Auffhammer and Mansur (2014) for a review of the empirical demand-side literature.

[2] In an Appendix, we re-estimate our primary regression results, and find agreement, under a range of alternative measures of weather scarcity.

panel of monthly emissions for each pollutant using data on emissions from tradable Air Markets Programs. We link these emissions to the water scarcity data discussed above. Again, our identification relies on exogenous variation in PDSI which correlates with a range of policy and physical linkages between water needs and electricity systems. Results suggest that water scarcity increases emissions of all three pollutants. We estimate the costs of induced CO_2 emissions alone to be more than $450 million per month (2015 dollars) if all plants in our sample were to experience a one-standard deviation increase in PDSI.

Looking forward, we take our econometric results and simulate generation under projections of water availability between 2051 and 2062. Although our results do not take into account changes in technology, infrastructure, or policy, we find that our primary results persist and strengthen slightly in response to anticipated levels of water scarcity. Thus, this exercise highlights the potential ongoing costs of water-electricity supply linkages under climate change.

Background

The effect of water scarcity on the electricity mix and on emissions depends on the extent to which incumbent electricity generators are susceptible to changes in water supplies as well as the availability and type of alternative generation sources (Meldrum et al., 2013). Electricity in the United States can be transported within three multistate interconnections: Western, Texas, and Eastern.[3] The composition of the electricity fleet in each interconnection differs because of such factors as historical accessibility to fuels and local and regional regulations (Table 1). In addition, water sources and cooling technologies vary among interconnections (Table 2). As a result, there is heterogeneity in both the exposure of the existing generation mix to water scarcity and in the type of power plant that will replace generation from water-intensive plants (Zivin et al., 2014). This heterogeneity in turn suggests that the effect of water scarcity on pollutant emissions will vary throughout the country (Muller and Mendelsohn, 2009).

Adaptation to water scarcity for thermoelectric power plants depends critically on available cooling technologies and water sources. A recent review by Macknick et al. (2012) surveyed water consumption and withdrawal needs for a range of power plant types.[4] Among nonrenewable sources, nuclear is generally the most water intensive, followed by coal and then natural gas. Hydroelectric generation and concentrated solar are the most water consumptive renewable electricity sources, while water needs for solar photovoltaic and wind are negligible. Water consumption also varies by cooling type. Water needs in plants using once-through cooling are much lower than those using cooling towers or ponds. Averyt et al. (2011) also document the vulnerability of power plants differentiated by water source. Surface water withdrawals from rivers, lakes, and oceans accounted for nearly all of the water (84 percent) used for thermoelectric cooling. Further, Newmark et al. (2010) note that additional environmental controls, particularly carbon capture and storage (CCS) systems, also increase water needs. Therefore, to the extent that water constraints lead to electricity responses, these responses may occur at both the interfuel and intrafuel level.

Such responses carry environmental and climatological implications. According to a summary of life-cycle fuel analyses by Moomaw et al. (2011), nuclear, hydroelectric, and renewable generation emits virtually no carbon dioxide (CO_2), whereas natural gas and coal emit 470 grams per kilowatt-hour (g/kW h) and 840 g/kW h, respectively. CO_2 emissions from natural gas and coal generation can be reduced if the plant operates a CCS system. Similarly, according to the EPA's Emission and Generated Resource Integrated Database (eGRID), nuclear, hydroelectric, and renewable generation emits negligible quantities of sulfur dioxide (SO_2) and nitrogen oxides (NO_x). Coal emits substantial amounts of both SO_2 and NO_x, whereas natural gas emits little SO_2 and approximately one-third the NO_x emissions of coal generation. If water scarcity reduces generation from nuclear, hydroelectric, or renewable sources in favor of coal or natural gas, emissions will rise. On the other hand, if water scarcity shifts generation from coal to natural gas, emissions will decline. Further, heterogeneity in water intensity within a given fuel type allows for yet another margin on which generation could affect emissions. We document evidence of fuel switching and corresponding changes in CO_2, SO_2, and NO_x that vary geographically in response to increasing water scarcity.

Data

We use several publicly available data sources in our empirical analysis. The first, used in our plant-level analysis, is a nearly comprehensive compilation of electricity generation in the United States for plants operating throughout 2001 and 2012. The second, used in our aggregate analysis, is a combination of plant-level emissions data from electricity producers in the US Environmental Protection Agency's (EPA) Air Markets Program (AMP) paired with climatic variables. Paramount to

[3] Electric utilities in each of the interconnections are connected electrically during normal system conditions and operate at a synchronized frequency.

[4] There is an important distinction in water use between withdrawals and consumption. Water withdrawals indicate uses of water that are diverted or withdrawn but returned to their original source, whereas water consumption is the use of water that is not returned to its source due to evaporation, transpiration, physical consumption, or similar processes.

Table 1
Generation statistics by Interconnection.

Fuel type	Percentage of total generation (number of plants)		
	Western	Texas	Eastern
Coal	35.8%	42.6%	59.0%
	(55)	(14)	(482)
Natural gas	18.4%	40.9%	9.7%
	(238)	(97)	(616)
Nuclear	9.5%	15.0%	25.2%
	(3)	(2)	(58)
Petroleum	0.2%	0.3%	1.5%
	(22)	(5)	(518)
Hydropower	31.8%	0.3%	3.5%
	(551)	(21)	(743)
Geothermal	2.4%	–	–
	(44)	–	–
Wind	0.8%	0.7%	0.1%
	(71)	(10)	(49)
Biomass	0.9%	0.2%	0.7%
	(65)	(6)	(169)
Solar	0.1%	–	–
	(13)	–	–
Other	0.1%	–	0.3%
	(13)	–	(121)

All statistics presented are percentages for the full sample spanning 2001 through 2012. Percentage of total generation by fuel type is presented along with the number of plants (in parentheses). Source: Authors' calculations.

Table 2
Water source and cooling technology statistics by interconnection.

	Interconnection		
	Western	Texas	Eastern
Water source:			
Ground	13.3%	8.4%	8.8%
Municipal	12.4%	15.5%	13.8%
Surface	55.5%	52.9%	55.9%
Other	18.8%	23.2%	21.5%
Cooling technology:			
Cooling pond	0.6%	16.1%	1.8%
Dry cooled	1.0%	1.3%	0.4%
Once-through	2.1%	7.1%	13.5%
Recirculating	17.2%	30.3%	14.4%
None	78.0%	45.2%	65.5%
Other[a]	1.2%	–	4.4%
No. of plants	1075	155	2756

Entries are proportions of plants with type of water source or cooling technology within each interconnection. The total number of plants in our sample is 3986.

[a] Other cooling type refers to plants for which no cooling type is indicated. Source: Authors' calculations.

our empirical analyses, we merge water scarcity data at the climate region level within both of our analyses. We aggregate each data source to the monthly level; our analysis spans 2001 to 2012 inclusive. By constructing a large panel in both dimensions, our empirical approach exploits rich temporal variation among a wide geographical range.

Plant-level generation

Monthly net generation data are obtained from Energy Information Administration (EIA) and Federal Energy Regulatory Commission (FERC) forms.[5] Following the EIA's categorization, fuel sources are designated as coal, natural gas, petroleum, hydropower, nonhydro renewables (i.e., nuclear, solar, wind, geothermal, biomass), and all other fuel sources. These data span January 2001 through December 2012.

[5] Net generation is total generation less generation used for plant operations.

Prior to 2008, information on net generation came from EIA-906, EIA-920, and FERC-423 forms. From 2008 onward, the information was consolidated onto the EIA-923 form. The data were merged from each form using a generator-specific identifier. The EIA-923 contains detailed information on primary fuel sources, prime movers, nameplate capacity, fuel cost receipts, location, and other generator-specific information.

The first and last year that each plant appeared on the EIA-923 is tabulated. For each generator, the sample is restricted to include only those plants that were in operation for the full timespan as indicated by EIA reports. We thus construct a balanced panel because modeling the opening and closing of plants explicitly is beyond the scope of this analysis; however, we do include plants that close for maintenance. As a sensitivity check, we also estimate our primary models on the unbalanced panel of plants.

We examine spatial heterogeneity by conditioning our analysis on regional electricity interconnections that define three broad electricity markets within the US. The three interconnections are Western, Texas, and Eastern. The Western interconnection incorporates all electricity produced, roughly, west of the Rocky Mountains. The Texas interconnection incorporates the majority of the state of Texas. The Eastern interconnection encompasses all other generators. Some electricity does move between interconnections, but this fraction is relatively small. Because we are interested primarily in generation decisions in response to local weather conditions, we do not model electricity transmission across the boundaries of the interconnections.

Generation is aggregated by fuel type within each plant. For example, if an operating plant maintains two coal–fired generators and three natural gas–fired generators, generation from both coal generators is aggregated and treated as a single plant-by-fuel-type observation. Additionally, the three natural gas generators are aggregated to a single monthly generation observation. Generation arising from different fuel sources within the plant are treated as independent observations.

Emissions data

Monthly emissions data are obtained from EPA's Air Markets Program data. The AMP data include hourly information on CO_2, SO_2, and NO_x emissions for every power plant that is subject to an air markets program. Emissions are aggregated to the plant-month level to match the climatic data. Again, when we use the term plant here, we are referring to a unique power plant-fuel combination. The number of plants included in the AMP has increased as additional air markets have been introduced. In 2001, 1146 plants comprising 3410 generators were required to report emissions. In 2012, 1534 plants comprising 4923 generators were required to report. We are able to match a total of 1392 plants from the emissions data to our plant-specific generator data and water scarcity data. The number of plants increases from 964 plants in 2001 to 1310 in 2012.

Water scarcity and weather variables

We obtain monthly water scarcity and climatic variables from the National Oceanic and Atmospheric Administration's (NOAA) National Climatic Data Center (NCDC). Water scarcity is measured using the Palmer Drought Severity Index (PDSI) and defined at the climate region level. A map of climate regions are presented in Fig. 1. Climate regions do not cross state boundaries and there are at most ten climate regions in a state. The PDSI is a hydrological measure of supply of and demand for soil moisture that captures drought trends. PDSI values are derived from precipitation (water supply) and temperature (potential evapotranspiration or water demand) and normalized to a range of $(-10, 10)$. Calculated PDSI is correlated with observable water data, such as soil moisture content and streamflow (Dai, 2011; Dai et al., 2004). Further, the PDSI is constructed to take into account past conditions, making the index inherently dynamic. In our sample, the PDSI varies roughly in the range $(-9, 9)$ in our sample, with negative values indicating water scarcity and positive values indicating water abundance. A PDSI value of −2 reflects moderate drought, −3 severe drought, and so on.

Temperature information is represented using cooling degree days (CDDs). CDDs are a non-linear measure of how far temperatures are from an ambient indoor reference temperature. The reference temperature is 65° Fahrenheit.

We plot CDDs relative to PDSI over time in Fig. 2 for each interconnection. As shown, the seasonal pattern in CDDs varies over time. Throughout our study period, we also capture several severe droughts that vary spatially. During each drought, some regions experience no drought or even water abundance, which aids in identification. An important takeaway is that the PDSI level moves independently of is measure of temperature. Because drought is a medium-term weather trend, its effect on electricity generation will be differentiated from weather patterns and seasonal demand shocks. This fact is central to our identification strategy: conditional on seasonal trends, temperature, and other demand shocks, the effect of changes in water scarcity on electricity generation is a plausibly exogenous shock to supply.[6,7]

[6] Further, there is no reason to believe that reverse causality would bias results within our study. Changes in generation in response to drought that affect carbon emissions are highly unlikely to have a short-run effect on the prevalence or severity of drought.

[7] In the appendix, we show that, after conditioning on NERC CDDs, there is no effect of average NERC PDSI on total NERC-level generation, which approximates total electricity demand (see Table A1).

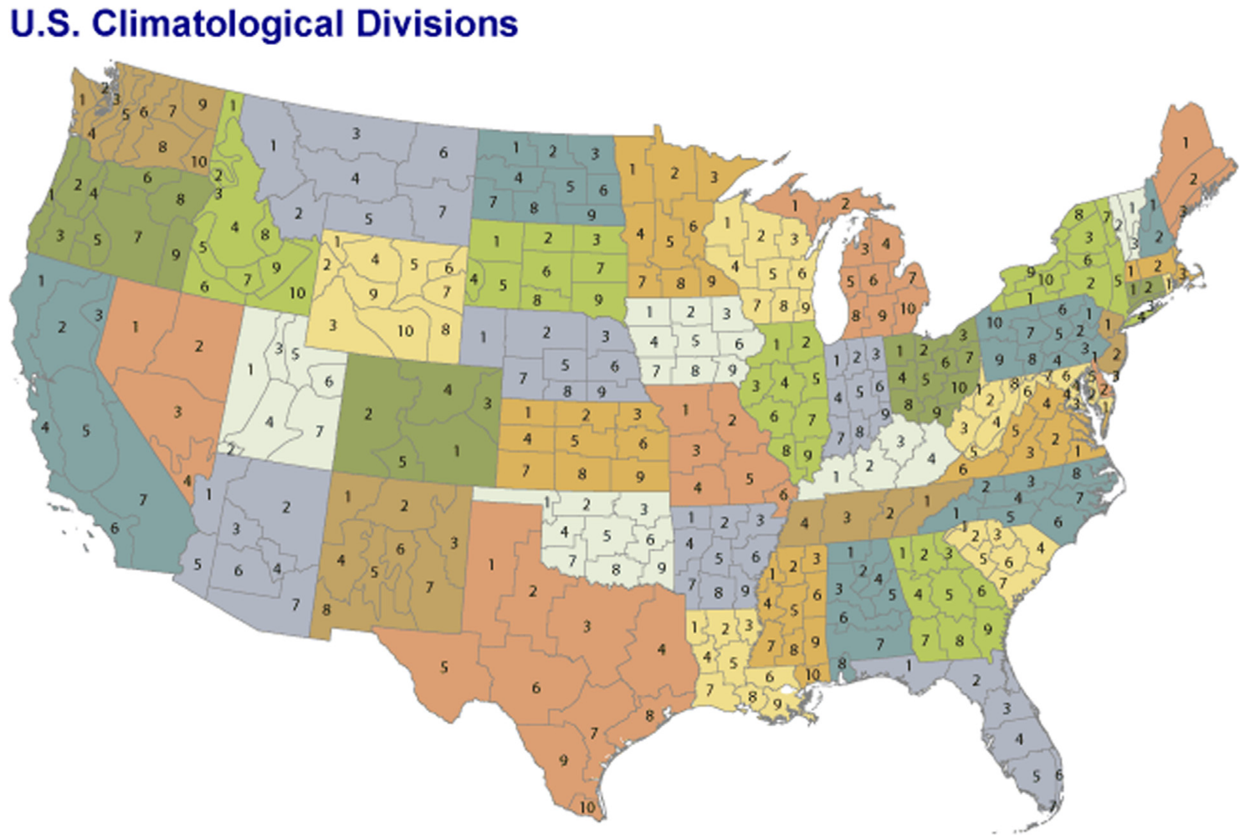

Fig. 1. National Climatic Data Center Climate Divisions in the United States.

Water sources and cooling technologies

Finally, we obtain water sources and cooling technologies used for all power plants in our sample from the Union of Concerned Scientists' UCS EW3 Energy-Water Database.[8] Using a variety of EIA sources, the UCS database links power plants to water use, water sources, and cooling technologies within the existing suite of electricity generators in the United States. We merge information from the UCS database to our time series of generation data at the plant-by-generator level to link generation with water use characteristics within a given plant.

In Table 2, we present summary statistics by water source and cooling technology at the plant level. As shown, plants relying on surface water withdrawals constitute the majority of our sample, while municipal and groundwater sources also account for a sizable portion of the distribution. Other sources could contain seawater or wastewater, for example, to cool power plants.

Cooling technologies for each plant are also tabulated in Table 2. The vast majority of plants have no cooling technology reported. These plants could be hydroelectric plants or natural gas combustion turbines, neither of which requires water for cooling. Recirculating cooling is the next most prevalent cooling type, followed by once-through cooling. Both of these metrics vary across interconnection regions. Cooling ponds and dry cooling towers constitute a smaller share of the cooling technologies used by the plants in our sample.

Methodology

Our empirical models exploit the conditional exogeneity of water scarcity as it affects generation and emissions. To that extent, we develop two independent analyses. In the first, we examine the effect of water scarcity on electricity generation at the plant level. Within these plant-level specifications, we analyze the importance of existing, and heterogeneous, capital

[8] Union of Concerned Scientists. 2012. UCS EW3 Energy-Water Database V.1.3. www.ucsusa.org/ew3database. Last accessed: April 11, 2014.

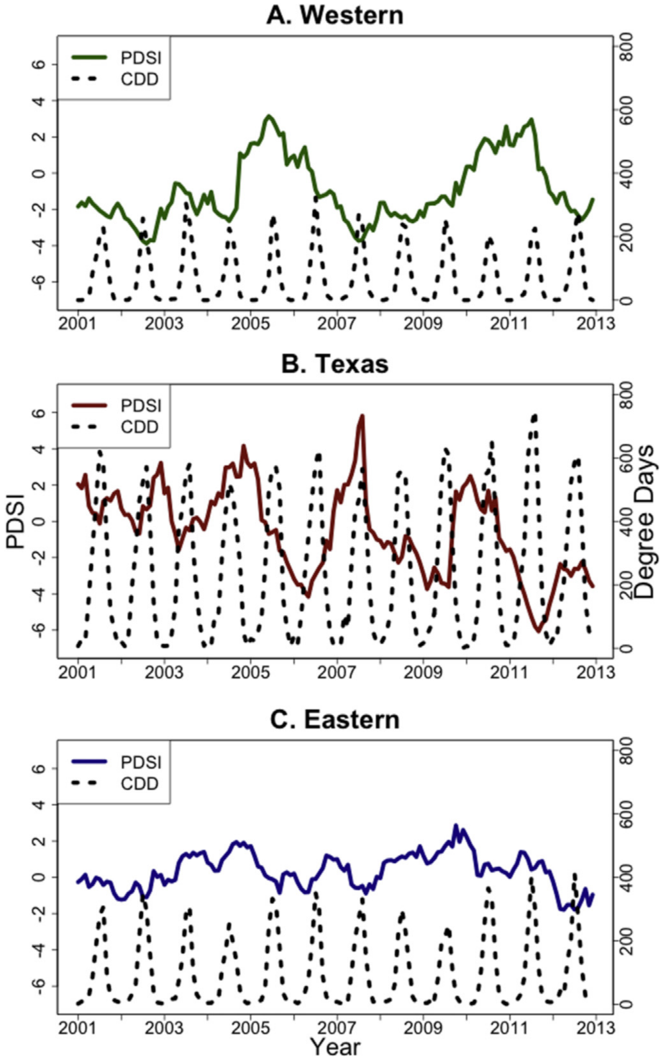

Fig. 2. Palmer Drought Severity Index (PDSI) over time relative to cooling degree days for each interconnection. Panel A represents temperature and drought variation in the Western Interconnection; Panel B represents temperature and drought variation in the Texas Interconnection; and Panel C represents temperature and drought variation in the Eastern Interconnection.

stock within an electricity market and its ability to react to changes in water scarcity. In the second, we provide a broader analysis of the effect of water scarcity on emissions of air pollutants.

Generation models

We identify changes in the United States electricity generation mix attributable to water scarcity econometrically. Our approach differs from the prior literature in which hydrologists and engineers employ either large-scale models that simulate climatic conditions based on a fixed generation stock (e.g., Vliet et al., 2012; Macknick et al., 2012) or narrower analyses that track the full life cycle of water in the production of electricity (e.g., Scanlon et al., 2013). In contrast, we use observed variation in water scarcity in the United States between 2001 and 2012 to identify changes in electricity generation disaggregated by fuel type and geography. Attribution of causality relies on the extent to which water scarcity shifts electricity supply exogenously after controlling for seasonal trends, temperature, and other contemporaneous demand shocks. Conditional exogeneity of water scarcity, in this context, is a plausible assertion.

To understand plant decisions in response to water scarcity, we estimate the effect of changes in PDSI on plant generation directly. We first specify a baseline panel model of net generation that controls for unobserved plant heterogeneity. Our baseline specification is

$$\sinh^{-1}(\mathrm{NetGen}_{irnt}) = \sum_{k\in K}\delta^k\left(\mathrm{PDSI}_{rt}\times \mathrm{Fuel}_i^k\right) + \theta\mathrm{CDD}_{rt} + \mathbf{X_{rnt}}\gamma + \alpha_i + \tau_t + \varepsilon_{irnt} \tag{1}$$

where NetGen_{irnt} is net generation for plant i in climate region r in interconnection n at time t. An inverse hyperbolic sine transformation ($\sinh^{-1}$) is applied to net generation. Essentially, parameter estimations from a $\sinh^{-1}$-linear model can be interpreted the same as that of a log-linear model for positive support and $\sinh^{-1}$ exhibits the desirable property of being defined at 0, because we do have true zero observations in our NetGen_{irnt} variable.[9] The inverse hyberbolic sine transformation is defined as $\sinh^{-1}(x) = \ln(x + (1 + x^2)^{1/2})$ and, except for very small values of x, is approximately equal to $\ln(2x)$. Hence, coefficients can be interpreted as (semi-)elasticities (Burbidge et al., 1988). We interact our drought index (PDSI_{rt}) with an indicator for each plant's fuel type k in the set of all available fuel types K. CDD_{rt} are cooling degree days at the region-month level. Plant and month-of-sample fixed effects are represented by α_i and τ_t. Plant fixed effects absorb any unobservable time-invariant characteristics of the plant, such as nameplate capacity, and allow comparisons among plants of varying sizes. Month-of-sample fixed effects control flexibly for changes in market characteristics, such as changes in relative fuel prices over time, that are not modeled explicitly because of data limitations. The residual error term (ε_{irnt}) is adjusted for autocorrelation at the plant level.

In our baseline specifications, we adjust the elements included in $\mathbf{X}_{rnt}$, α_i, and τ_t and observe how our parameters of interest, δ^k, evolve. Specifically, we include some combination of demand controls, including cooling degree days and total generation of electricity within an interconnection. The notion here is that after controlling for plant and month-of-sample fixed effects, if we fix demand at a given level, we can explain the residual variation in a plant's generation with variation in our drought indicator. Thus, the set of parameters δ^k provides estimates of the effect of changes in PDSI on plant-level generation conditional on fuel type k.

Regional heterogeneity

Because water scarcity affects the electricity sector differently depending on the capital stock and generation portfolio in a given energy market, we estimate our preferred models on subsets of the national market. We disaggregate the national market by three regional interconnections that are well-defined geographic markets. The benefit from estimating market-specific heterogeneity lies primarily in identifying the role of fuel switching in the short run, given an existing generation fleet. For the Western interconnection, for example, hydropower accounts for more than 30 percent of total generation and thus will respond differently from the Texas Interconnection, which generates less than one percent of its electricity from hydropower (Table 1). Thus, the national plant-level estimates conceal policy-relevant heterogeneity. The limitation of such an approach is that we ignore electricity transmitted across interconnections.

Drought severity, water sources, and cooling technologies

Thus far, we have limited the relationship between electricity generation and water scarcity to be linear and rather simplistic. We recognize that moderate drought may induce different responses from the electricity sector than catastrophic drought, which is analogous to nonlinear effects of temperature on economic activity (Burke et al., 2015). We also rely on the positive—that is, the water-abundant—portion of the PDSI distribution for identification. We are therefore concerned that our results may not fully reflect the extent to which water scarcity affects the generation mix.

We again estimate the inverse hyperbolic sine of net generation at the plant level, modifying our estimating equation as follows:

$$\sinh^{-1}(\mathrm{NetGen}_{irnt}) = \sum_{k\in K}\sum_{b\in B}\delta^{bk}\left(\mathrm{PDSI}_{rt}\times \mathrm{Bin}_{rt}^b\times \mathrm{Fuel}_i^k\right) + \theta CDD_{rt} + \mathbf{X}_{rnt}\gamma + \alpha_i + \tau_t + \varepsilon_{irnt}. \tag{2}$$

We decompose the PDSI distribution into six bins and construct a vector of indicator variables, Bin_{rt}^b, that equal one if a climate region's PDSI value falls in bin b and zero otherwise. The first bin captures PDSI_{rt} observations below −5; the second captures observations for $\mathrm{PDSI}_{rt}\in[-5,-2)$; the third, $\mathrm{PDSI}_{rt}\in[-2,0)$; the fourth, $\mathrm{PDSI}_{rt}\in[0,2)$; the fifth, $\mathrm{PDSI}_{rt}\in[2,5)$; and the sixth, $\mathrm{PDSI}_{rt}\geq 5$. Each bin corresponds, roughly, to drought indicators used widely for communicating drought severity to the public. These models are estimated to provide a sense of how the severity of drought (or water abundance) affects generation from different fuel sources heterogeneously. We recognize that this disaggregation restricts electricity generation to be linear within each bin. We leave a comprehensive analysis of the nonlinearities in the electricity sector's response to water scarcity, especially catastrophic drought, for future work.

Further, the extent to which an incumbent power plant is susceptible to changes in water scarcity depends on both its water source and cooling technology, both of which remain fixed for a given plant in our sample. Thus, although our panel estimation controls for this heterogeneity among plants, it also masks how plants with different water sources or cooling technologies might respond to drought differently. To examine heterogeneous responses to water scarcity along these

[9] The results are statistically similar if the inverse hyperbolic sine is replaced by the log of net generation plus 1. We present these results in Table A7 in the Appendix.

Table 3
Baseline regression results.

	(1) OLS	(2) Panel	(3) Panel	(4) Panel	(5) Panel	(6) Panel
PDSI × Hydro	0.062***	0.104***	0.096***	0.100***	0.094***	0.099***
	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
PDSI × Coal	0.027***	0.013*	0.013*	0.017**	0.013*	0.016**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
PDSI × Natural gas	− 0.144***	− 0.048***	− 0.055***	− 0.049***	− 0.055***	− 0.049***
	(0.004)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
PDSI × Nuclear	0.064**	0.016	0.012	0.015	0.011	0.014
	(0.027)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
PDSI × Solar	0.245***	0.039*	0.030	0.038	0.031	0.038
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
PDSI × Wind	− 0.038***	0.012	0.000	0.004	0.001	0.004
	(0.005)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
PDSI × Geothermal	− 0.149***	0.031	0.022	0.029	0.022	0.030
	(0.012)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)
PDSI × Biomass	− 0.054***	− 0.016	− 0.017	− 0.013	− 0.018	− 0.014
	(0.006)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
PDSI × Petroleum	− 0.389***	− 0.021***	− 0.032***	− 0.028***	− 0.032***	− 0.029***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
PDSI × Other	0.116***	− 0.037*	− 0.044**	− 0.041*	− 0.045**	− 0.042*
	(0.013)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
CDD				0.002***		0.002***
				(0.000)		(0.000)
Interconnection generation					0.000***	0.000***
					(0.000)	(0.000)
Observations	573,984	573,984	573,984	573,984	573,984	573,984
No. of plants	3986	3986	3986	3986	3986	3986
Within R-squared	0.013	0.006	0.033	0.036	0.034	0.036
Plant fixed effects?	N	Y	Y	Y	Y	Y
Month-of-sample fixed effects?	N	N	Y	Y	Y	Y

The dependent variable in each column is the inverse hyperbolic sine of net generation at the plant level. Column (1) presents results from an ordinary least squares regression. Columns (2)–(6) present results from the "within" fixed effects panel data estimator. "CDD" is cooling degree days. "Interconnection generation" is total electricity generation at the interconnection level. Standard errors in parentheses are clustered at the plant level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Authors' calculations.

dimensions, we estimate Eq. (1) including interactions of $PDSI_{rt}$ with indicator variables for the cooling type and water source of power plant i, respectively. These results provide insight into the vulnerability of different types of power plants while also highlighting ways the electricity sector can adapt to water shortages in the short to medium run.

Plant-level pollution models

Next we turn to a set of regressions that explore the relationship between water scarcity and emissions from the electricity sector. First, we rely on a model of plant-level emissions in the spirit of our plant-level generation regressions presented above. We estimate an unbalanced panel of monthly CO_2, NO_x, and SO_2 emissions, again controlling flexibly for weather, time, and time-invariant unobservable characteristics at the plant level. Our estimating equation is

$$\sinh^{-1}(\text{emissions}^{j}_{irnt}) = \delta \text{PDSI}_{rt} + \theta \text{CDD}_{rt} + \alpha_i + \tau_t + \varepsilon_{irnt}, \tag{3}$$

where $\text{emissions}^{j}_{irnt}$ is the level of emissions of pollutant type j for $j \in \{CO_2, NO_x, SO_2\}$ from plant i, in climate region r, in interconnection n, at time t. CDD_{rt} are cooling degree days as defined previously. α_i and τ_t are plant and month-of-sample fixed effects, respectively. And, ε_{irnt} is the residual error term. $PDSI_{rt}$ is the PDSI level for a plant-month observation based on the NCDC region of the plant. We are thus interested in the coefficient δ, as this will identify the effect of changes in water scarcity on realized emissions levels.

To explore this further, we again disaggregate our national models to identify region-specific effects. Specifically, we re-estimate Eq. (3) separately for each of the three Interconnects. We note that for SO_2 and NO_x, which are both flow pollutants, the damages that arise from electricity production occur reasonably close to their source of generation in both time and space (Muller and Mendelsohn, 2009). Emissions of SO_2 and NO_x also interact with other chemicals and physical processes; thus, we refrain from interpreting changes in emissions of these pollutants as changes in pollution. CO_2, being a stock pollutant, does not necessarily produce immediate damages in a given geography or time period. Thus, our region-specific results identify heterogeneity in the emissions of CO_2, NO_x, and SO_2 induced by water scarcity in the electricity sector.

Table 4
Fuel type regression results.

	Interconnection		
	Western	Texas	Eastern
PDSI × Hydro	0.087***	0.062	0.102***
	(0.009)	(0.043)	(0.007)
PDSI × Coal	0.006	− 0.038	0.018**
	(0.021)	(0.027)	(0.008)
PDSI × Natural gas	− 0.047***	0.007	− 0.070***
	(0.011)	(0.028)	(0.008)
PDSI × Nuclear	0.046	− 0.059*	0.014
	(0.143)	(0.030)	(0.017)
PDSI × Solar	0.042*		
	(0.024)		
PDSI × Wind	0.002	− 0.048	0.012
	(0.013)	(0.049)	(0.017)
PDSI × Geothermal	0.030		
	(0.020)		
PDSI × Biomass	− 0.023	− 0.112*	− 0.004
	(0.021)	(0.064)	(0.017)
PDSI × Petroleum	− 0.010	0.065	− 0.029***
	(0.031)	(0.150)	(0.006)
PDSI × Other	0.084		− 0.062***
	(0.052)		(0.024)
CDD	0.002***		0.002***
	(0.000)		(0.000)
Observations	154,800	22,320	396,864
No. of plants	1075	155	2756
Within R-squared	0.041	0.078	0.038
Plant fixed effects?	Y	Y	Y
Month-of-sample fixed effects?	Y	Y	Y

The dependent variable in each column is the inverse hyperbolic sine of net generation at the plant level. Standard errors in parentheses are clustered at the plant level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Authors' calculations.

Results and discussion

Our initial results for the full sample are presented in Table 3. Our empirical results suggest that increases in water scarcity (a decrease in the PDSI) reduce hydroelectric generation substantially. A one standard deviation decrease in the PDSI ($\sigma = 2.7$) results in an approximately 27 percent decrease in electricity generation at hydroelectric plants. This forgone hydroelectric generation is offset primarily by natural gas generation, resulting in a net 13.4 percent increase in natural gas generation per standard deviation increase water scarcity. At the national level, there is no statistically significant effect of water scarcity on either renewable or nuclear generation. These results are generally consistent across a range of controls for electricity demand and fixed effects. We focus on the specification presented in column (4), which includes cooling degree days as a control for electricity demand as well as month-of-sample and plant-fuel fixed effects for the remainder of our discussion. We prefer the specification with cooling degree days rather than interconnection generation because it is more easily comparable when we re-run our sample separately for each interconnection (interconnection-level generation is subsumed in month-of-sample fixed effects in these models).

A similar pattern is shown in Table 4 for the Western and Eastern Interconnections: drought-induced reductions in hydropower are offset primarily by increases in natural gas generation. Further, decreases in coal generation in the Eastern Interconnection are observed, suggesting potential shifting toward less-water-intensive fossil fuel generation (Macknick et al., 2012) or increased use of slow-ramping coal generation during periods of water abundance when hydro generators are readily available to provide ramping services. Because displaced hydroelectric generation is offset by fossil fuel generation rather than renewable or nuclear generation, carbon dioxide emissions from the electricity sector are likely to increase with increases in water scarcity.

As shown in Fig. 3, increases in water scarcity reduce generation from hydroelectric sources across the entire distribution of water scarcity in the Eastern and Western Interconnections. Each point in these graphs shows the marginal effect of PDSI (additional water abundance) on net generation for a particular fuel type. Moving from left to right, we show the marginal effect of additional water abundance on generation in extremely arid settings to extremely wet ones. In both cases, the marginal effect of changes in water scarcity is largest at the driest end of the water scarcity distribution, indicating that a change from moderate drought to extreme drought will reduce hydroelectric generation more than a change from extreme water abundance to moderate water abundance. There is some evidence that increased water scarcity results in decreased

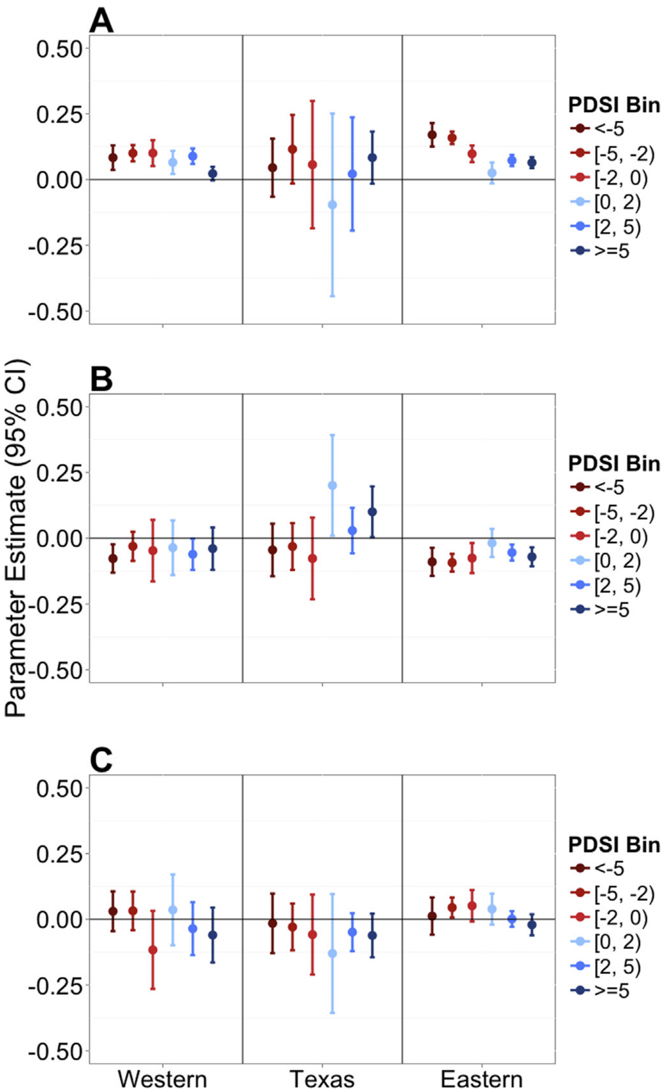

Fig. 3. Heterogeneity in generation by interconnection across the PDSI distribution. (A) represents hydroelectric generation; (B) represents natural gas generation; and (C) represents coal generation. Estimated coefficients are presented along with 95 percent confidence intervals. Estimates for all three subfigures are obtained from models estimated with two-way fuel type-by-PDSI bin interactions for each interconnection region separately.

hydroelectric generation in the Texas Interconnection; however, the results are not consistent throughout the distribution of the PDSI and they possess large confidence intervals. This result is likely due to Texas having very little hydropower In both the Eastern and Western Interconnections, natural gas generation increases as water scarcity increases, with the largest percentage increases occurring at the driest end of the water scarcity spectrum. This result is consistent with the use of natural gas to replace displaced hydroelectric generation.[10] The effect of water scarcity on coal generation is generally statistically insignificant. There is, however, some evidence in the Eastern Interconnection that increased water availability results in increased coal generation along some portion of the water scarcity distribution. This finding is consistent with switching from coal to natural gas electricity sources because of water scarcity because natural gas generators, in general, are less water-intensive than coal generators or with coal generators being forced to reduce generation at very low levels of water availability because hydro-power is unable to provide rapid ramping services.

Increased water scarcity results in decreases in electricity generation from plants that draw their water from surface water supplies in each of the three interconnections (Table 5). In the Eastern Interconnection, reductions in generation from surface water-based plants are met with increased generation from plants that use municipal water or groundwater. In the Western and Texas Interconnections, reductions in generation from plants using surface water are primarily met by

[10] As a sensitivity check, we run our primary model specification on the subset of our sample before the natural gas boom, in 2008. Results, presented in Table A6, are similar.

Table 5
Water source regression results.

	Interconnection		
	Western	Texas	Eastern
PDSI × Surface water	0.070***	0.019	0.043***
	(0.009)	(0.030)	(0.005)
PDSI × Municipal water	− 0.028**	0.006	− 0.052***
	(0.014)	(0.051)	(0.009)
PDSI × Groundwater	0.003	− 0.127***	− 0.049***
	(0.014)	(0.041)	(0.013)
PDSI × Other	− 0.007	0.027	− 0.025***
	(0.009)	(0.037)	(0.006)
CDD	0.002***		0.002***
	(0.000)		(0.000)
Observations	154,800	22,320	396,864
No. of plants	1075	155	2756
Within R-squared	0.038	0.040	0.014
Plant fixed effects?	Y	Y	Y
Month-of-sample fixed effects?	Y	Y	Y

The dependent variable in each column is the inverse hyperbolic sine of net generation at the plant level. Standard errors in parentheses are clustered at the plant level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Source: Authors' calculations.

Table 6
Cooling type regression results.

	Interconnection		
	Western	Texas	Eastern
PDSI × Once-through	− 0.070**	0.047	0.001
	(0.027)	(0.078)	(0.012)
PDSI × Recirculating	− 0.014	− 0.015	− 0.004
	(0.013)	(0.035)	(0.010)
PDSI × Cooling pond	− 0.149**	0.049	0.056***
	(0.064)	(0.045)	(0.016)
PDSI × Dry cooled	0.005	0.319	− 0.092
	(0.019)	(0.276)	(0.095)
PDSI × Other	0.085		− 0.063***
	(0.052)		(0.024)
PDSI × None	0.044***	− 0.015	0.012***
	(0.007)	(0.031)	(0.004)
CDD	0.002***		0.002***
	(0.000)		(0.000)
Observations	154,800	22,320	396,864
No. of plants	1075	155	2756
Within R-squared	0.037	0.041	0.012
Plant fixed effects?	Y	Y	Y
Month-of-sample fixed effects?	Y	Y	Y

The dependent variable in each column is the inverse hyperbolic sine of net generation at the plant level. Standard errors in parentheses are clustered at the plant level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Source: Authors' calculations.

increases in generation from plants using municipal water and groundwater sources, respectively. In terms of water cooling technology, increases in water scarcity in the Texas and Eastern Interconnections result in reductions from plants that do not require water for cooling and plants that use cooling ponds; in these regions water scarcity shifts generation toward plants that use dry cooling (Table 6). In the Western Interconnection, increases in water scarcity decrease generation from power plants that do not use water for cooling, and increase generation from plants using once-through cooling, recirculating cooling, or cooling ponds. In our data we observe hydroelectric plants as using no cooling technology, and the effect of water scarcity on generation at plants with no cooling technology is driven by this characterization.

Results from our emissions models suggest a net increase in CO_2, NO_x, and SO_2 emissions as the result of water scarcity (See the top of Table 7). A one-unit decrease in PDSI results in a 2.2% increase in plant-level monthly CO_2 emissions nationally, and smaller but statistically significant increases in SO_2 and NO_x emissions. The average plant in our sample emits approximately 160,000 tons of CO_2 per month, so a one-unit decrease in PDSI would increase plant-level monthly CO_2

Table 7
Water scarcity and electricity-sector emissions by plant at the national level.

Panel A:	CO_2	SO_2	NO_x
PDSI	− 0.022***	− 0.005**	− 0.007***
	(0.006)	(0.002)	(0.002)
CDD	0.003***	0.001***	0.002***
	(< 0.001)	(< 0.001)	(< 0.001)
Observations	173,082	173,082	173,082
No. of plants	1392	1392	1392
Within R-Squared	0.0057	0.0019	0.0165
Plant fixed effects?	Y	Y	Y
Month-of-sample fixed effects?	Y	Y	Y
Panel B:			
PDSI × Natural gas	− 0.049***	− 0.011***	− 0.021***
	(0.008)	(0.002)	(0.003)
PDSI × Coal	0.023**	0.006	0.017***
	(0.008)	(0.004)	(0.003)
PDSI × Petroleum	− 0.024	− 0.009	− 0.012
	(0.02)	(0.012)	(0.008)
PDSI × Biomass	− 0.015	− 0.024	− 0.02
	(0.017)	(0.037)	(0.016)
PDSI × Other	0.233	0.033	0.049
	(0.179)	(0.051)	(0.04)
CDD	0.003***	0.001***	0.002***
	(< 0.001)	(< 0.001)	(< 0.001)
Observations	173,082	173,082	173,082
No. of Plants	1392	1392	1392
Within R-Squared	0.0068	0.0023	0.0186
Plant fixed effects?	Y	Y	Y
Month-of-sample fixed effects?	Y	Y	Y

The dependent variable in each column is the inverse hyperbolic sine of emissions at the plant level. Standard errors in parentheses are clustered at the plant level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Source: Authors' calculations.

emissions by approximately 3500 tons. Based on a $36 per ton social cost of carbon (with a three percent discount rate) (Interagency Working Group on Social Cost of Carbon, 2015), the monthly effect of an increase in water scarcity of one-standard deviation. ($\sigma = 2.6$) is approximately $330,000 per plant-month (2015 dollars).[11] If all of the plants in our sample were to simultaneously experience a one-standard deviation decrease in PDSI the total social cost would be $457 million per month. NO_x and SO_2 emissions would increase by around 1.5 and 3 tons per month for each plant in our sample. The CO_2 and NO_x effect is largely driven by plants in the Eastern Interconnection (See the top of Table 8), while the SO_2 effect is driven by plants in the Western Interconnection (See the top of Table 9). There is not a statistically significant effect of PDSI on emissions in the Texas Interconnection for any of the three pollutants (See the top of Table 10).

When we disambiguate our emissions results by fuel type (See the bottom of Table 7), we find that water scarcity decreases emissions from coal plants and increases them from natural gas plants. This is consistent with our generation models. At the national-level, we find effects on SO_2 only from natural gas plants, but SO_2 emissions from natural gas plants are small so the result is negligible. Results are generally similar in the Eastern and Western Interconnections but in Texas the only statistically significant effect of PDSI on emissions appears in the effect of SO_2 emissions from natural gas plants. In the Western Interconnection, there is evidence of some reductions in CO_2 and NO_x emissions from petroleum plants as water becomes more scarce.

Sensitivity of primary results

We include several sensitivity analyses to affirm that our primary results are robust. Our largest concern is that PDSI is a proxy with little relevance to observable production constraints for electricity generation. Thus, we substitute three different measurements of water scarcity in our primary models: the Palmer Hydrological Drought Index (PHDI) from the NCDC; the quantity of county-level precipitation (Precip) and its one-period lag; and a measure of stream runoff at the climate-region level reported by the USGS (Runoff) and its one-period lag. The PHDI measures "hydrological impacts of drought (e.g., reservoir levels, groundwater levels, etc.) which take longer to develop and longer to recover from. This long-term drought index was developed to quantify these hydrological effects, and it responds more slowly to changing

[11] The standard deviation of PDSI differs slightly from the plant-level generation models because we omit plants that do not report emissions, such as hydro-electric generators.

Table 8
Water scarcity and electricity-sector emissions by plant in the Eastern Interconnection.

Panel A:	CO_2	SO_2	NO_x
PDSI	− 0.014**	− 0.003	− 0.008***
	(0.007)	(0.003)	(0.003)
CDD	0.003***	0.001***	0.002***
	(< 0.001)	(< 0.001)	(< 0.001)
Observations	134,766	134,766	134,766
No. of Plants	1099	1099	1099
Within R-Squared	0.0041	0.0015	0.0231
Plant fixed effects?	Y	Y	Y
Month-of-sample fixed effects?	Y	Y	Y
Panel B:			
PDSI × Natural gas	− 0.051***	− 0.010***	− 0.028***
	(0.01)	(0.002)	(0.003)
PDSI × Coal	0.029***	0.007	0.018***
	(0.009)	(0.005)	(0.004)
PDSI × Petroleum	− 0.019	− 0.011	− 0.014*
	(0.02)	(0.012)	(0.008)
PDSI × Biomass	− 0.013	− 0.026	− 0.021
	(0.022)	(0.036)	(0.016)
PDSI × Other	0.258	0.031	0.055
	(0.180)	(0.053)	(0.043)
CDD	0.003***	0.001***	0.002***
	(< 0.001)	(< 0.001)	(< 0.001)
Observations	134,766	134,766	134,766
No. of Plants	1099	1099	1099
Within R-Squared	0.0053	0.0019	0.015
Plant fixed effects?	Y	Y	Y
Month-of-sample fixed effects?	Y	Y	Y

The dependent variable in each column is the inverse hyperbolic sine of emissions at the plant level. Standard errors in parentheses are clustered at the plant level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Source: Authors' calculations.

Table 9
Water scarcity and electricity-sector emissions by plant in the Western Interconnection.

Panel A:	CO_2	SO_2	NO_x
PDSI	− 0.018	− 0.007**	0.003
	(0.013)	(0.003)	(0.004)
CDD	0.003***	0.0002***	0.001***
	(0.001)	(< 0.001)	(< 0.001)
Observations	25,848	25,848	25,848
No. of plants	213	213	213
Within R-squared	0.0079	0.0032	0.0200
Plant fixed effects?	Y	Y	Y
Month-of-sample fixed effects?	Y	Y	Y
Panel B:			
PDSI × Natural gas	− 0.039***	− 0.006**	− 0.003
	(0.015)	(0.003)	(0.005)
PDSI × Coal	0.050***	− 0.010	0.020**
	(0.018)	(0.008)	(0.010)
PDSI × Petroleum	0.115***	0.002	0.043***
	(0.014)	(0.002)	(0.006)
CDD	0.003***	0.0002***	0.001***
	(< 0.001)	(< 0.001)	(< 0.001)
Observations	25,848	25,848	25,848
No. of plants	213	213	213
Within R-squared	0.0097	0.0034	0.0213
Plant fixed effects?	Y	Y	Y
Month-of-sample fixed effects?	Y	Y	Y

The dependent variable in each column is the inverse hyperbolic sine of emissions at the plant level. Standard errors in parentheses are clustered at the plant level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Source: Authors' calculations.

Table 10
Water scarcity and electricity-sector emissions by plant in the Texas Interconnection.

Panel A:	CO_2	SO_2	NO_x
PDSI	0.009	− 0.005	0.003
	(0.028)	(0.004)	(0.004)
CDD	–	–	–
Observations	12,468	12,468	12,468
No. of plants	95	95	95
Within R-squared	0.0006	0.0038	0.00003
Plant fixed effects?	Y	Y	Y
Month-of-sample fixed effects?	Y	Y	Y
Panel B:			
PDSI × Natural gas	0.018	− 0.006**	0.002
	(0.029)	(0.003)	(0.015)
PDSI × Coal	− 0.035	0.017	− 0.003
	(0.034)	(0.018)	(0.015)
CDD	–	–	–
Observations	12,468	12,468	12,468
No. of plants	95	95	95
Within R-squared	0.0006	0.0038	0.00003
Plant fixed effects?	Y	Y	Y
Month-of-sample fixed effects?	Y	Y	Y

The dependent variable in each column is the inverse hyperbolic sine of emissions at the plant level. Cooling degree days (CDD) are omitted due to collinearity with month-of-sample fixed effects. Standard errors in parentheses are clustered at the plant level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Source: Authors' calculations.

Table 11
Changes in generation between 2001–2012 and 2051–2062.

	PDSI	Generation from:									
		Hydro	Coal	Natural gas	Solar	Geothermal	Wind	Nuclear	Biomass	Petroleum	Other
National	− 0.073	− 0.016	0.002	− 0.003	− 0.004	− 0.006	− 0.001	− 0.000	0.001	− 0.003	0.001
Western	− 0.171	− 0.024	− 0.004	0.013	− 0.004	− 0.006	− 0.001	− 0.000	0.004	0.009	0.006
Texas	− 0.258	− 0.039	− 0.009	0.006			− 0.001	− 0.004	0.006	0.010	
Eastern	− 0.024	− 0.007	0.002	− 0.005			− 0.001	− 0.000	0.000	− 0.003	0.001

Values in the PDSI column correspond to the change in average PDSI at each plant in the sample between the period 2001–2012 and the period 2051–2062. PDSI changes are expressed in PDSI units. Values in the generation columns correspond to the percentage change in average plant-month generation for a given fuel source between the period 2001–2012 and the period 2051–2062.

conditions than the PDSI."[12] Precipitation in a given location provides a measurement of instantaneous water availability, although it does not account for the seasonal dynamics of snow melt or river flows. Stream runoff, on the other hand, captures fresh water availability at the plant-level for those situated on rivers, but fails to characterize groundwater availability and its recharge. Each metric of water availability thus has drawbacks for use in this setting.

In the appendix, we re-estimate our primary regression model for the national sample, as well as for each of the three Interconnections accounting for each of these alternative definitions of water availability. We find consistent, statistically significant effects of water scarcity on hydro generation across each of the specifications, although the impact of a one-standard deviation increase in water availability is smaller in the precipitation and runoff models, likely because these variables capture shorter-term drought than does PDSI. In Table A2, results using PHDI rather than PDSI are nearly identical in sign and magnitude to our primary results, which suggests that accounting for longer-term drought does not affect our conclusions in an appreciable way. In Table A3, we do notice some discrepancies. In column (4), the coefficients on coal becomes negative, and the coefficient on contemporaneous natural gas generation is positive, but insignificant. In Table A4, however, we re-establish the signs and significance of our primary models using stream runoff as a measure of water availability. Given that precipitation is meant to proxy for stream runoff, and that runoff captures snow melt and other spatial dynamics of river flows, we place more confidence in these estimates as they agree with two of our other water scarcity metrics. We speculate that a longer-run average of precipitation may be useful for our application to account for seasonal flows, but it is unclear what would be gained from such an exercise beyond what is revealed by our alternative

[12] Source: https://www.ncdc.noaa.gov/temp-and-precip/drought/historical-palmers/overview. Last accessed: May 9, 2017.

measures of water availability.

We implement three final robustness checks. First, in the construction of our plant-level generation data set, we forced the panel to be balanced. We made this modeling choice to avoid the complications of modeling plant openings and closings, and their effect on our estimates. In Table A5, we show that re-estimating our plant-level models on an unbalanced panel does not affect our results in a meaningful way. Second, we are concerned that the drastic change in natural gas availability due to hydraulic fracturing may affect the generation fuel mix within our study. To test for this, in Table A6, we estimate our primary results on a subsample for time periods prior to 2008. Our results are robust to this stratification, which suggests sensibly that low natural gas prices are orthogonal to water scarcity's effect on electricity generation. Finally, in Table A7 we show that the selection of the inverse hyperbolic sine transformation, rather than the more common natural logarithm plus one approach, is not driving our results.

Electricity generation under future water scarcity

As a result of climate change, water scarcity and abundance patterns are expected to shift in the next century with droughts generally becoming more frequent and more severe. As water grows more scarce, the U.S. electricity mix will likely shift from relatively water-intensive sources of generation towards alternative sources of generation.

In order to consider the effect of changes in water availability on the electricity mix, we use our baseline model (Column (4) in Table 3) to calculate electricity generation at each of the plants in our sample under expected water availability patterns between 2051 and 2062. For each observation in our data set, we assign the corresponding PDSI value from 50 years into the future.[13] We then multiply these future PDSI values by the associated coefficients in our baseline regression and add them to the month-of-sample and power-plant specific fixed effects, as well as CDDs multiplied by the appropriate coefficient. This provides a predicted level of generation for each power plant assuming that water scarcity was equal to its expected level 50 years into the future. Note that regulations, the fleet of electric generators, fuel prices, consumer demand, and so forth will change between 2001–2012 and 2051–2062, so our results should not be construed as projections of generation in the future. Rather, our estimates correspond to predicted generation between 2001 and 2012 if each power plant had experienced its 2051–2062 level of water scarcity.

PDSI projections are obtained from Zhao and Dai (2015, 2016) who calculate monthly, global PDSI values between 1900 and 2100 at a 2.5 degree-by-2.5 degree resolution. We match each power plant to the surrounding four grid points and assign it the average of the (non-missing) PDSI values for the associated grid points. In order to ensure consistency, we calculate baseline generation levels using the imputed values of PDSI between 2001 and 2012, rather than the observed values from the observed NOAA climate data.

Average percentage changes in monthly plant-level generation are shown in Table 11. We observe moderate reductions in generation from hydro power plants under the 2051–2062 PDSI values. Average fitted monthly net generation falls from approximately 60,000 MW h to 59,060 MW h, a reduction of about 1.6%. Median hydro generation is largely unchanged from present levels. Generation from coal plants increases by approximately 150 MW h while natural gas generation falls by a comparable amount. Note that while our primary regression results indicate that coal generation falls with additional water scarcity and natural gas generation rises with additional water scarcity, the change in PDSI is spatially heterogeneous. This result is consistent with greater water availability in coal-reliant regions and less water availability in natural gas-reliant regions. The relatively small change in generation levels is unsurprising. The average change in PDSI for plants in our sample is only about -0.1.

The largest changes in PDSI are projected to occur in the Western and Texas Interconnections, with relatively small changes in the Eastern Interconnection. As such, the largest generation changes occur in these regions. Average monthly hydro-electric generation is projected to decline by 2.4 percentage points in the Western Interconnection and nearly 4 percentage points in the Texas Interconnection. Because of spatial heterogeneity in the impact of climate change on water availability, some areas may see increases in generation even among plants that co-vary positively with water availability. In the Eastern Interconnection, for example, our fitted values reflect moderate increases in coal generation even as water becomes more scarce. This effect is explained by relatively small increases in water availability in the regions of the Eastern Interconnect that have many coal plants, while the reductions in water availability that drive the overall reduction in water availability occur in other areas.

Conclusion

In this study, we uncover an effect of changes in water availability on the electricity mix, highlighting the potential short- and mid-term consequences of climate change–induced variation in water scarcity on electricity systems. Further, we identify an important feedback between water scarcity and CO_2 emissions.

[13] An observation corresponding to a power plant in January 2001 would receive the PDSI value associated with that power plant in January 2051, for example.

We find that a one-unit increase in PDSI results in an increase in hydroelectric generation on the order of 8 percentage points. We also note the critical importance of the type of fuel that replaces the foregone hydro power. We find that in much of the country, natural gas, rather than coal, is called upon when water scarcity increases. While we find some evidence that coal generation in the Eastern Interconnection falls as water scarcity rises, we generally find little movement in electricity sources other than hydro and natural gas. This suggests that water constraints—both physical and legal—facing coal and nuclear generators do not appear to have a binding effect in the data.

The environmental implications of water scarcity's effect on the electricity mix are decidedly mixed. While carbon-intensive coal generation does not seem to be increasing while water is scarce, there are still substantial increases in CO_2 emissions associated with the increased use of natural gas. These effects are on the order of several hundred thousand dollars per month for each plant that experiences a one-standard deviation reduction in PDSI.

Using projections of future PDSI, we find moderate reductions in hydro generation—approximately 1.6%—under 2051–2062 PDSI levels. There are relatively small changes in natural gas and coal generation under the projected PDSI values. The projected models of PDSI likely smooth out some of the variability in water availability, however, and these changes could be larger if water scarcity increases more appreciably or at the most sensitive portions of the distribution.

Interpretation of our results for policy purposes is subject to several caveats. First, long-run water scarcity or abundance will affect utility decisions about the construction of new power plants, affecting both the exposure of the electricity mix to water scarcity and the marginal source of electricity generation that will offset displaced generation (Tidwell et al., 2011). Similarly, in our analysis we assume that plant generation and hydroelectric water release decisions are made myopically. If water scarcity results in conservation of water sources, our estimates will be overestimated at the beginning of droughts and underestimated at the end of droughts relative to the “true” hydrological production limitation. Still, to the extent that policy is concerned with the response of the electricity mix to water scarcity, the result of interest is, in fact, inclusive of conservation behavior.

Our analysis casts novel light on a key issue at the heart of climate change adaptation—the nexus of water scarcity and the supply of electricity. Further research is needed on the direct implications of water scarcity on water sources and cooling technologies at the plant level, as well as broader studies of the regional, national, and global effects of the ability of the energy sector to adapt to water scarcity.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jeem.2017.07.002.

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