The Thirst for Power: The Impacts of Water Availability on Electricity Generation in China

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ABSTRACT

Economic development under restricted resource availability has become a complex challenge for both developing and well-established economies. To maintain a sustainable electricity supply and mitigate the impact of water shortage on economic development, it is therefore important to understand how utility firms respond to the change in water availability and unpacks the underlying mechanisms of power outage. By pairing plant-level information with the fine-scale grid monthly meteorological data, we find significant plant-level technology substitution in response to water scarcity: a one-standard-deviation decrease in water availability causes an approximate 205 GWh decline per hydro power plant, a 145 GWh increase per nuclear plant, and a 28 GWh increase per coal-fired plant. This water-induced technology substitution takes place within the grid, and we do not identify cross-grid adjustment. Our estimation shows that the technology substitution is associated with a hidden increase in carbon emission up to 32000 tons per year by plant, resulting in an additional cost of 0.18 million USD. Water scarcity slows down the transition towards renewable energy.

Keywords: Water availability, Drought, Water scarcity, Technology substitution, Electricity shortage, Power outage

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1. INTRODUCTION

Economic development under restricted resource availability has become a complex challenge for both developing and well-established economies. The availability of resources, like water, has been drastically affected by global warming with increased frequency in droughts and heat waves (Milly et al. 2005; Olmstead 2010), which lowers agriculture production (Mendelsohn et al. 1994) and disrupts international trade (Debaere 2014). More damagingly, electricity supply becomes unreliable due to increased water temperature and reduced water availability, as water is both directly used for power generation in hydropower plants, and indirectly for cooling in thermal and nuclear generation. Firm productivity has been significantly limited by the increased electricity scarcity (Fisher-Vanden et al. 2015). To maintain a sustainable resource supply and mitigate the impact of water shortage on economic development, it is therefore important to understand how utility firms respond to the change in water availability and unpacks the underlying mechanisms of power outage.

This paper addresses this by investigating the technologies that utility plants use to generate electricity. Although the correlation between frequent droughts and persistent electricity short-

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ages is well known, it remains unclear as to how and why electricity shortages are related to drought. Relevant studies on this relationship are scant, especially for developing countries, possibly because meteorological data on water shortage and temperature at the power plant level are not readily available. Furthermore, the literature is silent on whether the technology switch for cooling and power generation can be attributed to a decline in water availability. This lack of information reduces the efficiency of investment decisions in new technologies, as the technology substitution that is induced as a result of water shortages may be different from the choices suggested in the engineering models. Although generation capacity has increased significantly since the early 2000s, electricity shortages remained a major challenge for China in the early 2010s. It is reported that the prolonged drought in spring intensified the electricity supply in Hainan province in 2007. In addition, lower water level in Yangtze River triggered the decline in hydro power generation. Thus, the drought in central China leads to electricity brownouts and power rationing in 2011. In all, the electricity shortage lasted for almost whole year, with a cumulative power rationing of about 35.2 billion kWh in China (Yue, 2021). As an essential input for production, electricity shortages can lower firm revenue by 10% (Allcott et al. 2016) or increase production costs by 8% (Fisher-Vanden et al. 2015).

In this study, we match a plant-level panel of electricity generation information with a fine-scale monthly meteorological dataset on electricity generation, installed capacity, and water-use characteristics, relevant social economic factors of individual plants, and climatic information for plant locations for the period from 2007 to 2014. The unique dataset makes it possible to identify the mechanism behind the connections between water availability and electricity shortage, which can provide important information for managerial practice for achieving sustainability with restricted resource constraints. This is because water is the necessary resource for most plants in China. Hydropower generation requires large quantities of water to be available to operate the turbines. In addition, water is the major source for cooling in thermal power plants and nuclear plants.

To shed light on the channels through which an electricity shortage is related to drought, we apply a fixed-effect model to study the substitution effect of variations in water shortage on plant generation technology selection. Causal attribution in this paper relies on the extent to which water shortage variations affect electricity supply exogenously after controlling for cooling degree days, installed capacity, electricity price, and fixed assets investment. We follow Couttenier and Soubeyran (2014), Eyer and Wichman (2018) to use Palmer Drought Severity Index (PDSI) as a proxy for water scarcity. PDSI values are computed using observed air temperature and precipitation and self-calibrated dynamically with the climate and duration factors to capture spatially comparable long-term drought trends (Alley 1984; Dai 2011b; Dai 2017). In addition, we employ two alternative proxies for water scarcity: the Standardized Precipitation Evapotranspiration Index (SPEI) for the relative long-term and precipitation (P) for the short term. Precipitation in a given location measures the instantaneous water availability in the plant's surroundings, while the PDSI and SPEI are widely used indexes that incorporate past and current supply of precipitation and demand for potential evapotranspiration moisture, and capture the impact of global warming on drought severity (Dai 2011a, 2017; Vicente-Serrano, and National Center for Atmospheric Research Staff 2015). In this paper, water scarcity and draught are interchangeable terms used, and both terms indicate the decline in water availability. We show that based on fuel type, coal and nuclear are called upon to substitute for the forgone hydropower when water availability declines.

We find that a one-standard-deviation decrease in water availability causes an approximate 205 GWh decline in hydro power generation, a 145 GWh increase in nuclear generation, and a 28 GWh increase in coal generation. To minimum the estimation biases stemming from omitted variables, we also control for time invariant firm fixed effects, year-of-sample fixed effects, power grid region by year, and fuel type by year fixed effects in all our estimations. The results are robust for alternative measures of the water scarcity index. We also rule out factors that may confound our results on the technology substitution, such as newly constructed generators and regular generator maintenance.

To support our findings, following Chen and Yang (2019), we further construct quarterly average water scarcity as an alternative measure. The finding is consistent with that of using annual data. We also find that water scarcity may result in electricity shortages in the second and third quarters of a year in particular due to a technology shift. In addition, we introduce water availability bins to address the monthly nonlinear relationship between the severity of water scarcity (abundance) and power generation. A remarkable finding is that electricity generation responds positively to severe drought or extreme wet. We note that a change from moderate drought (moisture) to extreme drought (moisture) enhances electricity generation, especially coal-fired generation. Moreover, we analyse the effects of the characteristics of water withdrawal mechanisms for generators. Specifically, we focus on the water sources the plants rely on and the technology that the plants have installed to cool generators. We identify that technology selection in China's electricity sector is likely to move from relatively water-intensive generation technologies towards less water-intensive technologies. Our result is consistent with prior studies (DeNooyer et al. 2016; Eyer and Wichman 2018). By examining the spatial effects of water scarcity on technology substitution across grids, we find that water scarcity-induced electricity shortages cannot be alleviated by supply from other grids via inter-grid transmission, which may suggest that the inefficiency of the power grid dispatch and transmission system is another reason for the frequent power shortages that occurred in the early 2010s in China.

In addition, we address the environmental consequences of the technology selected for electricity generation induced by water scarcity (Amor et al. 2014; Clancy et al. 2015; Jacobsen and Schröder 2012). As discussed by Moomaw et al. (2011) in their lifecycle fuel summary analyses, coal-fired plants emit 840 g/kWh carbon dioxide, whereas hydroelectric and nuclear power plants emit little carbon dioxide. If droughts lead to a shift from the relatively water-intensive fuel source of hydro power towards nuclear or coal, emissions will rise accordingly. Hence, it is necessary to clarify to what extent the increased coal-fired generation resulting from drought results in rising greenhouse gas emissions. Our results suggest that the rising use of coal for electricity is associated with an increase in CO_2 emissions. The results imply a hidden increase in carbon emission up to 32000 tons of each thermal power plant per year, resulting in an additional cost of 0.18 million USD. We also note that a change from moderate drought to extreme drought would sharply intensify CO_2 emissions. An additional month at $(-\infty, -5)$, $[-5, -3)$, $[-3, -1)$, $[-1, 1)$ $[1, 3)$, $[3, 5)$, and $[5, \infty)$ bins of PDSI can lead to a substantial increase in average yearly CO_2 emissions from each coal power plant by roughly 27064 tons, 12632 tons, 9071 tons, 6404 tons, 2517 tons, 499 tons and 12078 tons, respectively.

In the literature, there are a growing number of studies that have estimated the effect of climate change on the energy sector (Rübbelke and Vögele 2011; Van Vliet et al. 2012; Olmstead 2014; Li et al. 2019; Zhou et al. 2019; Craig et al. 2019). Most of the existing studies apply non-econometric approaches, including lifecycle assessment (Gao et al. 2019), engineering models (Feeley III 2008; Rübbelke and Vögele 2011), and integrated assessment (Khan et al. 2016; DeNooyer et al. 2016), with a focus on developed regions (Miara et al. 2017; Behrens et al. 2017). With access to well-documented micro-level data, climate variations associated with human adaptation activities are an emerging trend in the studies (Auffhammer and Aroonruengsawat 2011; Barreca et al. 2016; Li et al. 2019). However, water shortage as an increasing resource availability concern has received little attention. An exception is Eyer and Wichman (2018), who used monthly plant-level data for the period from 2001 to 2012 to estimate the influence of water scarcity on the fuel mix in electricity generation. They find that the generation of hydroelectricity substantially decreases as water becomes scarce. This paper provides the very first quantitative investigation of the impact of water scarcity on electricity generation in a developing country.

Our study extends the related literature in several ways. Firstly, it contributes to an understanding of technology selection with restricted resource input in the process of transition towards greener economy. Morales-España et al. 2021 identify the situations when curtailing variable renewable energy (VRE) reduces both costs and CO2 emissions and conclude that VRE should be dispatched in an optimal way to maximize their value rather than output. Levi and Nault (2004) examined how heterogeneity in the operating condition of firms' plant and equipment can affect choices related to conversion to a cleaner technology. They find that firms with superior resources, such as plant and equipment being in better condition, will convert to a cleaner technology and vice versa. Bretschger and Zhang (2017) studied technology substitution in response to climate policy under restricted input use, while Xie and Zilberman (2018) found that investment in technology adoption for water-use efficiency and water-storage capacity has the potential to address the water scarcity issues and support firms in adapting to climate change. To guarantee a sufficient electricity supply in peak hours, Boomhower and Davis's (2020) study showed that energy-efficiency investments in air conditioning can help to reduce electricity consumption in the summer months.

Secondly, the paper contributes to the understanding of how the government responses to climate shock. China's electricity industry is dominated by five giant generation corporations and is a relatively monopolistic sector (Wang and Chen 2012). The five corporations are government controlled. The power plant sample used in this study were those plants with installed capacity of over one gigawatt (GW) that are affiliated with the five giant generation corporations, which means the sample studied largely represents the government's response behaviour, as all plants are controlled by the government. Electricity generated from power plants covered in our sample accounts for 44.1% of total power generation in China. Archsmith (2020) estimated the spillover effects of environmental regulation that forces hydroelectric dams to allocate electricity generation in an inefficient way over time. Meanwhile, a number of studies have demonstrated the efficiency issues associated with a monopoly market structure (Stewart 1980; Misiolek 1980; Hart 2004; Qiu et al. 2018). In this paper, the efficacy of government response to drought is measured by looking into the decisions related to electricity generation technology substitution, which is different to the study undertaken by Eyer and Wichman (2018), which estimated the market response of individual generators.

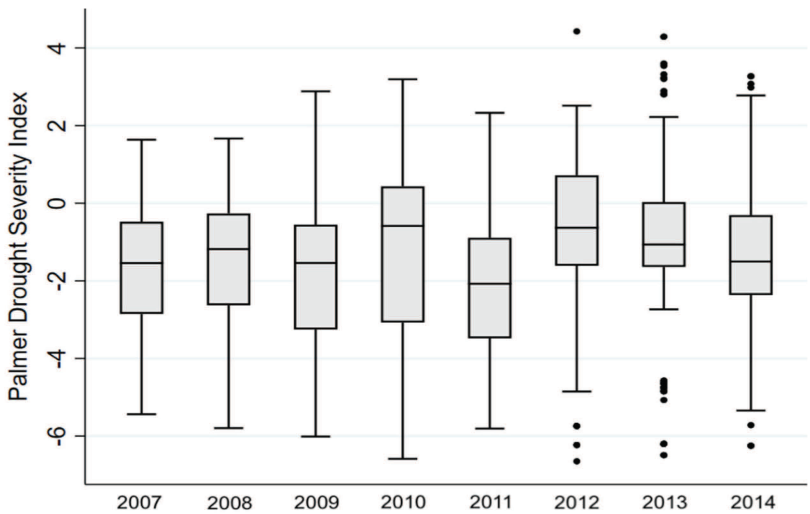
Thirdly, this paper identifies the underlying mechanisms for the severe electricity shortages in China in the early 2000s by linking water scarcity with electricity generation technologies. Using coarse macro data, Zhang et al. (2017) and Zheng et al. (2016) estimated the mismatch between water availability and power generation at province level in China. Although Wang et al. (2019) used detailed power plant data and a water scarcity index (water withdrawal to availability ratio) across the water basin scale, they used a non-econometric approach to quantify the influence of inter-grid electricity transmission on water scarcity risk. Building on Eyer and Wichman (2018), we pair annual plant-level generation with a resolution grid fine-scale monthly meteorological dataset for the period 2007–2014.

2. **BACKGROUND INFORMATION**

2.1. Water scarcity and electricity generation in China

Figure 1 portrays the Chinese yearly average water shortage from 2007 to 2014 inclusive using PDSI as a proxy for water scarcity. A negative PDSI value indicates a water shortage. The negative values provided in the figure are the highest-profile evidence that China has experienced drought to different extents. We also observe both extreme drought and extreme wet weather from 2012 onwards, as shown by the dots in the figure.

Figure 1: Degree of drought in China over time



Note: Figure represents Chinese yearly average water shortage over time. The lines inside the boxes show the median value. The lower and upper hinge of the boxes present the 25th and 75th percentiles of the variables. The whiskers on the bottom and top display the lower and upper adjacent values, respectively. The outside values are plotted with dots.
Source: The Climate Data Guide (2019), China Electric Power Yearbook (2008–2015).

As depicted in Appendix figure AF2(a), there is a positive correlation between PDSI and monthly electricity generation in China. That is, increased water scarcity, as shown by the lower PDSI index, is associated with a reduction in electricity generation. In Appendix figure AF2(b), it is noted that during the 2008–2016 period, the growth rates of both hydroelectricity and coal-fired generation fluctuated; however, they had opposing trends. It is likely that there exists a technology substitution between hydro and coal generation. Although the correlation between generation mix and water shortage is well known, the magnitude by which the hydropower generation is curtailed and the extent to which there is substitution of technologies under state control are not well identified. Appendix figure AF2(c) shows China's total CO_2 emissions and the CO_2 emissions of the electricity sector in China (Research Council UK 2007–2014). The data indicate that the emissions originating from the electricity generation sector account for approximately half of the total CO_2 emissions for China. Therefore, the decisions made around technology selection in response to water shortages will inevitably carry environmental implications.

2.2. Relative monopoly in China's electricity industry

The Chinese power industry has experienced three phases of market-oriented reform: absolute monopoly, breaking absolute monopoly, and relative monopoly (Wang and Chen 2012). Since 2003, China's power industry has been separated into the power generation section and the power grid section, which subsequently resulted in the current relative monopoly. The five giant generation corporations, which are central state-owned corporations, are the China Huaneng Group, the China Huadian Corporation, the China Guodian Corporation, the China Datang Corporation, and the China Power Investment Corporation. These corporations have a leading role in generation asset ownership and expansion of generation capacity. It is noted that in 2011, the five giant generation corporations controlled 49% of the installed capacity and other central state-owned generators controlled 11% (State Electricity Regulation Commission [SERC] 2011). These two utilities were owned by the State-owned Assets Supervision and Administration Commission (SASAC). In this sense, in 2011, the central state-owned generators accounted for 60% of the national installed capacity. Figure 2(a) shows the location of power plants at city level. The majority of power plants covered in this study are in the eastern cities of China.

Meanwhile, the nationwide transmission, distribution, and retail assets are controlled by two transmission companies, the State Grid Corporation of China and the South Power Grid Company Limited. The distribution of the individual grid systems is displayed in Figure 2(b). Under the management systems for generation and utilization, the government determines a generation target for a month and a year. It also has a daily generation dispatching schedule according to generator load (Gu and Xiao 2018). With regard to establishing the consumer price for electricity, instead of reflecting the generation costs, the price is set with reference to historical prices determined by the government (Lin and Liu 2013; Sun and Lin 2013). Therefore, there is still little competition in the Chinese power industry, and supply and demand do not affect the price. In this context, there is little independent adjustment undertaken in power generation by the plants, with government regulation behaviour playing a critical role in the decisions about technology substitution for power generation as water grows more scare.

2.3. Water requirements in distinguished electricity technologies

Adaptation of thermal power plants to water shortages relies predominantly on the characteristics of the cooling technologies employed and the nature of the water sources (Meldrum et al. 2013). A review by Zhang et al. (2016) examined the water withdrawal and consumption features of the different thermal electricity generation technologies in China. There is a distinction between water withdrawal and water consumption. Water withdrawal is the amount of water diverted or taken from a river, lake, or aquifer that is ultimately returned to the water source, whereas water consumption is the use of water from a source that is lost from the cycle due to processes such as transpiration or evaporation. Hydropower generation is the most water-consuming electricity technology. In China, the water losses using this technology are attributed to dam design, where water consumption for hydroelectricity generation mainly occurs from evaporation from reservoirs. Hydropower generation also requires large quantities of water to be available to operate the turbines, but this water is usually then used downstream by the agricultural sector (Rodriguez et al. 2013). Generally speaking, nuclear power is the most water withdrawal intensive of the non-renewable thermal power plants, followed by coal-fired power.

Moreover, the level of water consumption depends on the type of cooling system being used. Power stations that use a once-through cooling system consume the least water, followed by those that use a dry-cooled system. Power stations that use a recirculating system consume the most water resources; however, the once-through cooling system withdraws the most fresh water of the three systems. Zhang et al. (2016) also documented the characteristics of the water sources. In China, the water requirements for nuclear power generation are derived from seawater. They distinguish several types of freshwater sources: surface water, ground water, municipal wastewater, and mine water. Surface water accounts for 96% of the total fresh water, and once-through cooling plants withdraw large volumes of surface water. Hence, the range of requirements for water related to the type of fuel used and the nature of the cooling system will result in different technological responses during periods of water constraint.

3. EMPIRICAL STRATEGY

Several econometric power plant-level generation models are employed to identify the ability of power plants to react to the variation in water scarcity. We construct average drought variables from annual, quarterly, and monthly perspectives. The empirical analysis therefore involves three models, and this section provides an explicit description.

3.1. Yearly average indicators as water scarcity variables

Yearly average water scarcity variables are firstly implemented to help understand how changes in the electricity generation mix are attributed to water shortage. Causal attribution in this context relies on the extent to which water shortage variation affects electricity supply exogenously after controlling for temperature, characteristics of power plants, and contemporaneous electricity demand dominated by government policy. We first specify a benchmark panel model of electricity generation in Equation (1):

$$\ln Gen_{it} = \sum\nolimits_{k\in K} \beta^k \left(Water\,Scarcity\,Indicator_{it} \times Fuel_i^k \right) + \Theta X_{it} + \partial_i + \delta_t + \Psi_t^r + \Phi_t^k + \varepsilon_{it} \quad (1)$$

where power plants are indexed by i, power grids are indexed by r and k and t denote fuel type and years, respectively. The natural log of electricity generation for plant i in year t is denoted by $\ln Gen_{it}$. We interact the water shortage indexes with a dummy variable for each plant's technology k in a set of all three fuel types k. In our benchmark specifications, we evolve a vector of control variables included in X_{it}. Specifically, X_{it} contains a nonlinear climatic variable for cooling degree days ($CDDs_{it}$), characteristics of power plants captured by installed capacity (IC_i), and indicators for contemporaneous electricity demand dominated by government policy that involve electricity price ($Price_{it}$) and fixed assets investment (IS_{it}). $CDDs_{it}$ reflects the effect of a global warming-induced increase in cooling demand. is of importance as electricity power generation has a high reliance on it. Furthermore, the electricity industry in China is mainly dominated by government regulation, and thus determinants related to electricity demand led by government authority should be taken into consideration. We introduce two additional variables: on-grid electricity price set by local authority () and the stock of electricity source investment that could promote electrical power development ().

We control for four fixed effects to capture unobserved heterogeneity of time, plant, technology, and power grid region. Plant and year-of-sample fixed effects are denoted by and . Following Bai (2009), we incorporate another two interactive fixed effects: interaction between year and power grid region and year and fuel type, which are indexed by and , respectively. controls for the time-invariant plant characteristics that are unique to each power plant , such as geographical location. flexibly removes unobserved market demand factors that vary over time, such as coal fuel price. absorbs unobserved time-varying characteristics that are common to all electricity plants in a given year but differ across power grid region, such as changes in electricity or trade policies for a certain power grid region . Similarly, captures unobserved common factors for power plants in a given year but allows for time-varying heterogeneous technology for fuel types, such as the introduction of a new production technology that improves generation efficiency that is specific to fuel type . is the residual error term adjusted for autocorrelation at the power plant level. It captures the impacts on electricity generation of other factors that are excluded in Equation (1).[1] In our models, we are interested in estimating the set of parameters to determine how generation shifts among different technologies.

3.2. Quarterly average indicators as water scarcity variables

Most regions in China have four distinct seasons. The climatic variable for water scarcity indexes and temperature could change significantly over a year. We then follow Chen and Yang's (2019) measurement of seasonal average temperatures and adopt quarterly average water relevant indicators to gain a detailed understanding of the effect of seasonal water variations on power generation.

The yearly average water scarcity indexes are separated into four quarters. We incorporate the interaction between quarterly average water shortage indicators and fuel types for coal and hydro because the electricity generation of these two kinds of technologies rely heavily on the fluctuations in seasonal trends. We again estimate the generation portfolio at the plant level after controlling for the same set of effects as in Equation (1), revising our estimating equation as follows:

$$\begin{aligned} \ln Gen_{it} = & \sum\nolimits_{q\in Q} \sum\nolimits_{k\in K} \beta^{qk} \left(Water\ Scarcity\ Indicator_{it}^{q} \times Fuel_{i}^{k} \right) \\ & + \Theta X_{it} + \partial_i + \delta_t + \Psi_t^n + \Phi_t^k + \varepsilon_{it} \end{aligned} \tag{2}$$

3.3. Drought index bins as water scarcity indicators

Thus far, we assume the relationship between power generation and water shortage to be linear at yearly and quarterly level. However, the degree of drought severity, such as moderate drought and extreme drought, may trigger different responses from electricity producers. We divide the range of PDSI values into several bins. The number of months in year when the monthly PDSI falls into the th drought severity bin in a climatic grid where power plant is located is labelled as .

is when the monthly PDSI is below –5, represents the months falling into the range of [–5,–3), captures the observations for the number of months falling into [–3, –1) and , and capture the number of months falling into the range of [–1,1), [1,3), [3,5) and [5,), respectively. A positive PDSI distribution indicates abundant water conditions. Thus, the results examined in this study are concerned not only with the effect of water scarcity but also with the impact of water abundance.

Next, we construct a vector of indicator variables for the interaction between the yearly average PDSI and its distribution bins, which allows us to investigate the monthly causal relationship linearly and continuously within each bin. Meanwhile, this model provides a nonlinear estimation of

1. To adjust the within heteroscedasticity and serial correlation issue as discussed in Cameron and Miller (2015), we cluster the standard errors in the presence of a power plant-level effect.

how the severity of drought or water abundance affects electricity generation. In addition, we interact the established indicator variables with the coal technology dummy variable to further identify the nonlinear effects on coal generation. Our estimation equation is:

$$\begin{aligned}\ln Gen_{it} = &\sum\nolimits_{b\in B}\sum\nolimits_{k\in K}\beta^{bk}\left[Water\,Scarcity\,Indicator_{it}\times Bin_{it}^{b}\left(\times Fuel_{i}^{k}\right)\right] \\ &+\Theta X_{it}+\partial_i+\delta_t+\Psi_t^n+\Phi_t^k+\varepsilon_{it}\end{aligned} \tag{3}$$

3.4. Characteristics of water use based on water sources and cooling technologies

How an incumbent power plant responds to water shortages depends not only on the fuel types, but also on the characteristics of the water sources it uses and the related water-cooling technologies. To identify how water scarcity affects the choice of technology in terms of water sources and cooling techniques, we construct a vector of interactions between and indicator variables for the water-use characteristics of power plant after controlling for a set of fixed effects as in Equation (1). In this way, we obtain in-depth information on how the water source and cooling technique features of a technology respond to heterogeneous water scarcity. Equations (4) and (5) show the new model specification:

$$\begin{aligned}\ln Gen_{it} = &\sum_{c\in C}\beta^{c}\left(Water\,Scarcity\,Indicator_{it}\times Cooling\,Technology_{i}^{c}\right) \\ &+\Theta X_{it}+\partial_i+\delta_t+\Psi_t^r+\Phi_t^k+\varepsilon_{it}\end{aligned} \tag{4}$$

$$\begin{aligned}\ln Gen_{it} = &\sum_{w\in W}\beta^{w}\left(Water\,Scarcity\,Indicator_{it}\times Water\,source_{i}^{w}\right) \\ &+\Theta X_{it}+\partial_i+\delta_t+\Psi_t^r+\Phi_t^k+\varepsilon_{it}\end{aligned} \tag{5}$$

4. DATA

In this paper, we construct a unique, fine-scale, plant-level panel that contains data on electricity generation, installed capacity, and water-use characteristics, relevant social economic factors of individual plants, and climatic information for the plant locations for the period from 2007 to 2014. Table 1 provides the summary statistics. The key variables of electricity generation, water scarcity, climatic variables, as well as the cooling technologies and water source variables are described in detail in the following subsections.

4.1. Electricity generation variable

The study sample consists of 195 coal-fired power plants, 25 hydroelectric power plants and 5 nuclear power plants. Annual electricity generation information is collected from the *China Electric Power Yearbook* published by the National Bureau of Statistics (NBS) (2008–2015). This yearbook provides production statistics for power plants with installed capacity of over one GW. Fuel sources are primarily classified as coal, hydro, or nuclear following the plant's own categorization. This study tabulates the power plant generation data from 2007 to 2014. Meteorological data for the years after 2014 that match with the electricity generation data were unavailable. To obtain balanced panel data, the sample is restricted to plants that were in operation over the full timespan. Thus, newly built and closed plants were not analyzed.

Table 1: Data statistics description

Variables (Units)	Mean (Standard Deviation)	Minimum	Maximum	Source
Plant-month sample				
PDSI (--)	–1.43 (2.32)	–8.08	6.77	The Climate Data Guide (2019)
SPEI (--)	0.01 (1.02)	–2.59	2.69	The Climate Data Guide (2019)
Precipitation (cm)	8.20 (9.06)	0.00	118.59	Terrestrial Air Temperature and Precipitation (2017)
Plant-year sample				
Electricity generation (GWh)	8469 (64.01)	133	98293	China Electric Power Yearbook (2008–2015)
Cooling degree days (degree days)	94.35 (107.96)	0.00	576.50	Terrestrial Air Temperature and Precipitation (2017)
Installed capacity (GW)	1.69 (1.43)	1.00	22.40	China Electric Power Yearbook (2008–2015)
Province-year sample				
Price (constant 2007 yuan/10^3 kWh)	350.85 (70.73)	158.87	660.15	Electricity Pricing Supervision Report (2008–2015)
Stock of electricity source investment (constant 2007 10^8 yuan)	490.47 (352.57)	0.00	3100.00	Almanac of China's Waterpower (2008–2015) & Compilation of Statistical Materials of Electric Power Industry (2009–2011 & 2014)

4.2. Water scarcity and climatic variable

We obtain the monthly meteorological information from The Climate Data Guide of the National Center for Atmospheric Research (NCAR) (2019) and the Terrestrial Air Temperature and Precipitation of the National Oceanic and Atmospheric Administration (NOAA) (2017). We extract multiple proxies for water scarcity, which are measured by applying PDSI, SPEI, and P. The database consists of monthly global observation station data in a 2.5 × 2.5 degree grid for PDSI from January 1850 to December 2014 and a 0.5 × 0.5 degree grid for SPEI, precipitation, and air temperature from January 1900 to December 2014. Based on the geographical location of the power plants, we paired plant-level generation with water scarcity and climate variables over the observed period of 2007 to 2014. The proxies for water scarcity in our study do not consider human impacts on the water balance, hence they can be viewed as plausibly exogenous variables.[2]

Precipitation in a given location measures the information on instantaneous water availability in a plant's surroundings, while the PDSI and SPEI are widely used indexes that incorporate the past and current supply of (precipitation) and demand for (potential evapotranspiration) moisture that capture the impact of global warming on drought severity. The PDSI index dynamically self-calibrates the climate and duration factors to maintain consistent behaviour. Thus, it is more spatially comparable to quantify long-term drought trends (Dai 2011b; Dai 2017). PDSI is normalized and ranges from –10 to +10. Negative PDSI values demonstrate water scarcity while positive values indicate water abundance. A value of –2 mirrors moderate drought and values below –3 represents severe to extreme drought conditions. In the yearly estimation, we first normalize the monthly PDSI into the range of [0,1][3], then take the average in a year to match the yearly electricity generation data.

Similar to PDSI, SPEI accounts for the effects of precipitation and reference evapotranspiration, but it allows comparison of drought severity across time and space due to its multi-scalar nature (Vicente-Serrano and National Center for Atmospheric Research Staff 2015). SPEI is a standardized variable that obeys a normal distribution with an average value of 0 and standard deviation

2. Eyer and Wichman (2018) have elaborately verified that reverse causality is highly unlikely to exist.
3. The study normalizes the PDSI using the strategy $PDSI^* = \frac{PDSI-min}{max-min}$.

of 1, and can be calculated on a range of timescales from 1 to 48 months. With longer timescales of more than 18 months, it correlates with the self-calibrated PDSI indicator. In our research, we capture the SPEI using a one-month timescale approach.

To reflect the growing warming trend, we obtain the temperature information using cooling degree days (CDDs). CDDs are a nonlinear measurement of how surface air temperature deviates from an ambient indoor reference temperature. In the empirical analysis, we set a reference temperature of 26 °C.

We portray the fluctuation of national monthly average temperature, precipitation, PDSI and SPEI during the study period in Appendix figures AF3(a) and AF3(b). As shown in the figures, the seasonal mode in the temperature and water shortage indexes changes over time. We explicitly capture the average degree and relative level of water shortage from the trajectory of variation in the PDSI and SPEI in China temporally. These two indexes evolve over time independent of temperature.

Since drought is a medium to long-term climatic trend, the impact of variation in water scarcity on electricity generation will be distinguished from other weather features, seasonal patterns, and demand shocks. In our empirical study, we examine the causality by adopting the PDSI measure, as it covers more information than the SPEI. As precipitation captures the short-term water availability, PDSI overcomes the drawback of the metric of precipitation failing to account for the seasonal dynamics of water flow. Therefore, we use PDSI as the main proxy for the analysis, while the results of SPEI and precipitation are used for comparison.

4.3. Non-climate variables

Information on installed capacity for each power plant is obtained from the *China Electric Power Yearbook* (NBS 2008–2015). The average installed capacity for coal, hydro and nuclear electricity plants in this study is 1.6 GW, 2.4 GW, and 1.9 GW, respectively. For coal-fired plants, the maximum and minimum capacity are 4.8 GW and 1.0 GW, respectively. The installed capacity of hydroelectricity plants ranges from 1.0 GW to 2.2 GW. The lowest and highest installed capacity of nuclear power plants are 1.3 GW and 2.6 GW, respectively.

Due to the limitations of data availability, other non-climate factors are estimated based on province-level datasets. *Electricity Pricing Supervision Report* (SERC 2008–2015) releases the price at provincial level and by generation fuel types. The on-grid electricity price is set to be the same for power plants located in the same province and using the same fuel type.

The *Almanac of China's Waterpower and Compilation of Statistical Materials of Electric Power Industry* (NBS 2008–2015) reports the provincial-level investment by fuel source in the electricity sector. We apply the conventional perpetual inventory strategy[4] to calculate the stock of investment in electricity generation by fuel source. After that, each power plant's investment stock is approximated according to the ratio of its installed capacity to that of the sum of installed capacity in our sample within each type of fuel power generation in that province. All monetary non-climate variables are deflated to constant 2007 prices by a consumer price index.

4. The investment stock is calculated by applying the conventional perpetual inventory strategy. $K_{jt} = (1-\sigma_j)K_{j,t-1} + \Delta K_{jt}$, $K_{i0} = I_{j0}\,(1+g_j)/(g_j+\sigma_j)$, where K_{jt} denotes the real investment stock of province j in year t, ΔK_{jt} is the real incremental capital stock and σ_j is the rates of depreciation in each province (taken from Wu (2009)). K_{i0} and I_{j0} are the initial capital and investment stock and g_j denotes the province-specific growth rates of investment, which are replaced with average GDP growth rates.

4.4. Cooling technologies and water source variables

Details on cooling technologies and water sources used for the power plants in the sample are drawn from the *Materials of National Energy Efficiency Benchmarking Competition for Thermal Power Units 2012* (China Electricity Council [CEC] 2013). The database in this report links power plants to cooling technologies, water sources, and other technical parameters. We distinguish water-use characteristics within a given plant by cooling technologies or water-use sources when the plant runs several thermal power generators.

In China, 18.5% of generators in operation adopts air cooling and 81.5% uses water cooling technology (Zhang and Li, 2020). Among all water cooling technologies, once-through technology for generators is mainly used in the coastal area with relatively low investment costs, while recirculating cooling technology can fit all kinds of natural circumstance and is the most adaptive technology. Air-cooling technology is the most expensive one and mainly located in water shortage area like northwest and northern China. The two grid corporations will coordinate the type of cooling technology within the grid according to water withdrawal quotas set by government.

We match time-invariant water-use information with the time series of generation data at the plant level. The summary statistics by cooling technologies and water source for each power plant are provided in Appendix table AT1. Once-through and recirculating systems are the two traditional and most prevalent cooling types. Dry and hybrid-cooled technology, classified into *Other III for coal* type, account for a sizable share of cooling technologies. *Other II for hydro* shows cooling technologies for hydro turbines, which do not require water for cooling. *Other III for nuclear* refers to the cooling technology for nuclear fuel.

In terms of water sources, the *Other* group refers to coal plants that do not withdraw water and all hydro plants. The *Seawater* group is mainly for nuclear power plants. Appendix table AT1 shows that more than one third of coal plants rely on surface water withdrawal, followed by seawater and groundwater withdrawal. Municipal wastewater withdrawal constitutes a small portion of the distribution in the sample.

5. RESULTS AND DISCUSSION

5.1. Main results

The benchmark results are presented in Table 2, with the estimation based on yearly data. The results for PDSI as the water scarcity indicator show strong evidence of a substantial decline in hydroelectric generation when water scarcity increases (a reduction in the PDSI). From columns (2)–(4) in Table 2, we find that most estimated coefficients of the PDSI variable exert significant effects on the electricity generation mix and are generally consistent in sign and magnitude across a range of fixed effects model specifications. Meanwhile, we show a significant increase in coal and nuclear generation, implying a substitution between technologies.

Specifically, a one-standard-deviation reduction in PDSI results in an approximate 205 GWh decline in power generation in per hydro plant. The decrease in hydroelectricity generation is mainly offset by nuclear and coal-fired electricity generation. A one-standard-deviation decrease in PDSI (σ=2.32) causes a 145 GWh increase in nuclear generation in per nuclear plant and a 28 GWh increase in coal generation in per coal plant. The displaced hydroelectricity cannot be fully offset by thermal power generation and there is a 32 GWh electricity shortage for the substitution

Table 2: Baseline results

Dependent variable Ln(generation)	Model _ PDSI baseline							
	(1)		(2)		(3)		(4)	
PDSI × Coal	–0.129**	(0.060)	–0.104*	(0.060)	–0.132**	(0.065)	–0.097	(0.061)
PDSI × Hydro	0.635***	(0.166)	0.762***	(0.168)	0.457	(0.324)	0.595**	(0.241)
PDSI × Nuclear	–0.985***	(0.354)	–0.730*	(0.416)	–1.366***	(0.378)	–1.130***	(0.405)
Ln(CDD)	0.022	(0.019)	0.025	(0.022)	0.023	(0.020)	0.029	(0.022)
Control variables	Yes		Yes		Yes		Yes	
Observations	1800		1800		1800		1800	
No. of coal plants	195		195		195		195	
No. of hydro plants	25		25		25		25	
No. of nuclear plants	5		5		5		5	
Within R-squared	0.111		0.110		0.107		0.104	
Plant fixed effects	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
Power grid ×Year fixed effects	No		Yes		No		Yes	
Power plant type ×Year fixed effects	No		No		Yes		Yes	

Notes: The table presents results from the fixed effects panel data estimation. The dependent variable is the logarithm of power generation at the plant level. The key independent variables are interactions between yearly average PDSI and fuel type. CDD is a nonlinear climatic variable for cooling degree days. Other control variables contain installed capacity, electricity price and fixed assets investment. Robust standard errors adjusted for clustering at the power plant-year level are in parentheses. The sample spans 2007 through 2014. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of per power generation in China during the sample period, which means with increasing drought, electricity shortages may become more frequent and severe.

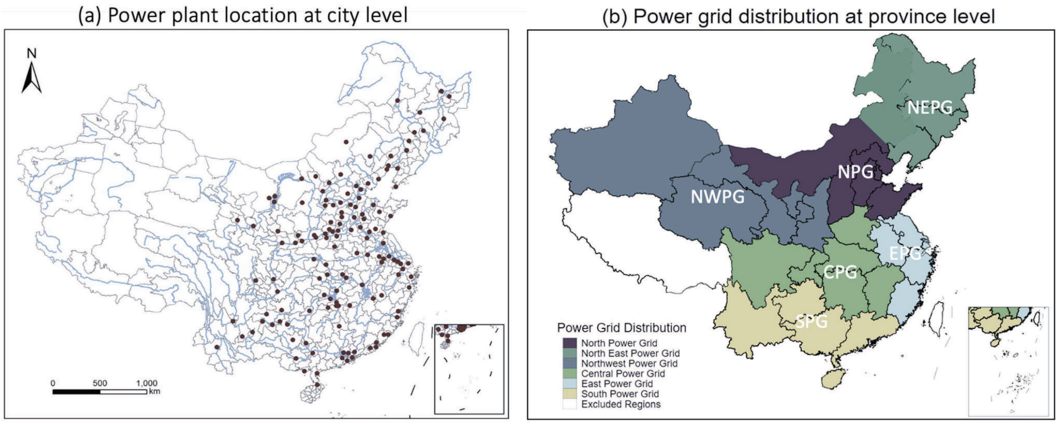
The industrial sector accounts for more than half of total electricity consumption. The firm productivity will be significantly affected by the increased electricity shortage. In fact, the electricity shortage also reflects the quality of power supply in a given period. In January of 2011, the reported power shortage exceeds 30 million kW all over China and nineteen provinces had to implement electricity rationing. Many factories in Zhejiang province had to take the action of "shutting down for one day for every three-days operation". This led to significant economic losses for both the firms and the country.

We are also aware that so far our discussion focuses on the supply shortage. The demand for electricity may fall at the times of drought. The power shortage attributed to drought could be over-estimated. For example, when suffering from drought climate, the electricity demand from the agricultural sector would fall accordingly. However, as agricultural sector consumes only 2.2% of total electricity, the change in demand could be relatively small.

In addition, drought could increase the demand for groundwater pumping and the demand for cooling. This implies that droughts may have more serious consequence then what we expect. In our model, CDD represents the non-linear measure of temperature and reflects the variations in electricity demand in the presence of temperature change. The coefficients of CDD in Table imply that 1% increase in CDD is associated with up to 0.03% rise in electricity generation. Compared with the coefficients of water scarcity index, CDD shows a relatively marginal effect on electricity generation. However, the positive effect of CDD indicates that the seasonal climate factor may increase the demand for electricity and may cause more brownouts or power crises during the drought climate.

We then identify the plants located near ten major rivers shown in Figure 2(a) and estimate whether the baseline results are sensitive to drought with different local river conditions. We find all the 25 hydro plants are located near the major rivers in China. 135 out of 195 coal-fired plants are close to the major rivers. As nuclear plants located in coastal area and mainly withdraw seawater for

Figure 2: Spatial distribution of power plant and power grid



Notes: (1) The dots in Figure 2(a) display the location of power plants investigated in this study. We use one dot in a specific city to represent the power plants located in the same city. The bold blue lines show the ten major water systems in China. (2) Figure 2(b) overlays the power grid of China. NEPG represents the northeast power grid, consisting of Liaoning, Jilin, Heilongjiang and the eastern part of Inner Mongolia. NPG represents the north China power grid, consisting of Beijing, Tianjin, Hebei, Shanxi, Shandong and the western part of Inner Mongolia. NWPG represents the northwest power grid, consisting of Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. EPG represents the east China power grid, consisting of Shanghai, Jiangsu, Zhejiang, Anhui and Fujian. CPG represents the central China power grid, consisting of Jiangxi, Henan, Hubei, Hunan, Sichuan and Chongqing. SPG represents the southern power grid, consisting of Guangdong, Guangxi, Guizhou, Yunnan and Hainan. Although NEPG, NPG, NWPG, EPG and CPG belong to State Grid Corporation of China, inter-grid transmission is limited. Due to lack of sufficient data, Tibet, Taiwan, Hong Kong and Macao are excluded from this research.

cooling, we thus exclude nuclear plants from the sample. We construct a dummy variable for coal plants located near the major rivers in China (the major rivers run through the cities where the plants are located) and interact it with water shortage index. The results are shown in Table 3. We identify that the decrease in water availability declines hydro electricity generation significantly. For coal power generation, it is less affected by water shortages when it closes to the river. However, coal plants far away from major rivers tend to increase the generation to substitute the decline in hydro generation, as they are less affected by water availability.

We also find regional disparity in electricity shortages across six grid regions, which means with increasing drought. The southern power grid (SPG) shows the highest level of electricity shortage associated with water scarcity. The results are displayed in Table 4.

Although nuclear generation may consume more water resources than coal-fired generation (Rodriguez et al. 2013; Zhang et al. 2016), nuclear power stations are mainly located in the south-east coastal area and use seawater instead of fresh water. It is therefore much easier for nuclear plants to adapt to the declining availability of water resources for nuclear power generation. More importantly, the central government advocates that the transition from fossil fuels to clean technology for power generation (World Nuclear Association 2020). As the China Electricity Council (2012) reported, aggregate power generation increased by 11.7% in 2011 compared with 2010, with hydro generation decreasing by 3.5% and coal and nuclear generation increasing by 14.1% and 16.9%, respectively.

China has been managing the utilization of scarce water resources in the power sector, including strategies for water withdrawal standards, water drawing permits and water resources fee, to decline water use intensity in coal power generation. Additionally, when water availability decreases, the two Grid Corporations—the State Grid Corporation of China and China Southern

Table 3: Water scarcity effect on technology by location

Dependent variable Ln(generation)	Model _ location (1)		Model _ location (2)		Model _ location (3)		Model _ location (4)	
PDSI × Coal× Non-river	–0.277***	(0.084)	–0.212**	(0.085)	–0.301***	(0.078)	–0.239***	(0.087)
PDSI × Coal× Major-river	–0.079	(0.058)	–0.067	(0.062)	–0.083	(0.056)	–0.055	(0.063)
PDSI × Hydro	0.638***	(0.165)	0.771***	(0.167)	0.458*	(0.233)	0.601**	(0.239)
CDD	Yes		Yes		Yes		Yes	
Control variables	Yes		Yes		Yes		Yes	
Observations	1800		1800		1600		1600	
No. of coal plants	195		195		195		195	
No. of hydro plants	25		25		25		25	
No. of nuclear plants	5		5		5		5	
Within R-squared	0.112		0.111		0.108		0.104	
Plant fixed effects	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
Power grid × Year fixed effects	No		Yes		No		Yes	
Power plant type × Year fixed effects	No		No		Yes		Yes	

Notes: The table presents results for effects of water scarcity on fuel type by location. The dependent variable is the logarithm of power generation at the plant level. The key independent variables are interactions between yearly average PDSI, fuel type and dummy variable for plants located near the major river or not. CDD is a nonlinear climatic variable for cooling degree days. Other control variables contain installed capacity, electricity price and fixed assets investment. No interactions for hydro plants as all the 25 hydro plants are close to the major rivers in China. Robust standard errors adjusted for clustering at the power plant-year level are in parentheses. The sample excludes nuclear power plants and spans 2007 through 2014. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Spatial heterogeneity of electricity shortage

Power grid region	PDSI (SD)	Coal (GWh) Increase	Hydro (GWh) Decrease	Nuclear (GWh) Increase	Electricity Shortage (GWh)
Total	2.32	28	205	145	32
NPG	1.93	23	171	121	27
NEPG	2.75	33	244	172	38
EPG	1.90	23	168	119	26
CPG	2.06	25	182	129	29
NWPG	2.09	25	185	131	29
SPG	2.88	34	255	181	40

Notes: SPG represents the southern power grid. NPG represents the north China power grid. EPG represents the east China power grid. NEPG represents the northeast power grid. NWPG represents the northwest power grid. CPG represents the central China power grid.

Power Grid, will coordinate and reallocate the type of cooling technology for power generation within power grid according to water withdrawal quotas set by government (Zhang, et al., 2016). Thus, nuclear and coal generation will provide ramping services to meet aggregate consumption.

Our results shed light on the inefficiency of the dispatch system in China to some extent. Different from the "merit order" dispatch approach where generators are dispatched in order of increasing variable cost of operation, the "fair" dispatch system has long been used in China where generators are allocated administratively the same annual utilization hours. Although the efficiency-based dispatch system began as a pilot in some provinces, they have faced strong opposition from coal-fired power plants as the new dispatch makes coal-fired plants losers in the market and exacerbates imbalances in the electricity supply (Kahrl et al. 2013). Many provinces have switched back to the administrative planning dispatch system; therefore, when water scarcity induces a reduction in hydroelectric generation, the flexibility to switch to alternative generators is low. The extra supply from other generators is thus not enough to meet the demand, resulting in an electricity shortage.

In China, coal fired plants contribute to over 60% of total power generation (Zhang, et al., 2016). The rule of "fair order" creates an economically inefficient dispatch system. Under this circumstance, a significant amount of cheap variable renewables (VRE) electricity generation is curtailed to meet the target full-load hours of conventional generation. Even without suffering from drought climate, the VRE like wind, photovoltaic and hydro electricity generation is replaced by more expensive fossil fuels on the basis of allocated generation hours especially in the Northwest and North Central regions (IEA, 2019). Therefore, technology substitution we have estimated may not be entirely attributed to drought events. The inefficiency of the dispatch system in China may also be one of the reasons for the substitution.

5.2. Alternative measures of water availability

As demonstrated in Table 5, when we replace the water scarcity index for PDSI with SPEI or precipitation, the main results are broadly robust. A statistically significant reduction in hydro power generation is observed when using SPEI or precipitation as the water shortage index. It also shows a potential shift towards less water-intensive fossil fuel technology in the electricity sector in China.

Table 5: Results for alternative water scarcity indicators

Dependent variable Ln(generation)	Model _ SPEI				Model _ Precipitation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SPEI(P) × Coal	–0.385***	–0.382***	–0.324***	–0.312**	–0.001***	–0.000	–0.001**	–0.000
	(0.084)	(0.132)	(0.086)	(0.127)	(0.000)	(0.000)	(0.000)	(0.000)
SPEI(P) × Hydro	0.035	0.243	–0.390	–0.219	0.002	0.003	0.001	0.002
	(0.336)	(0.361)	(0.450)	(0.511)	(0.003)	(0.003)	(0.003)	(0.004)
SPEI(P) × Nuclear	–0.718*	–0.532	–0.984**	–0.791*	–0.001	0.000	–0.001	0.000
	(0.433)	(0.440)	(0.458)	(0.473)	(0.001)	(0.001)	(0.001)	(0.001)
CDD	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1800	1800	1800	1800	1800	1800	1800	1800
No. of coal plants	195	195	195	195	195	195	195	195
No. of hydro plants	25	25	25	25	25	25	25	25
No. of nuclear plants	5	5	5	5	5	5	5	5
Within R-squared	0.108	0.104	0.106	0.100	0.105	0.102	0.103	0.097
Plant fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Power grid × Year fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Power plant type × Year fixed effects	No	No	Yes	Yes	No	No	Yes	Yes

Notes: The table presents results for alternative water scarcity indicators. The dependent variable is the logarithm of generation at the plant level. The key independent variables are interactions between fuel type and alternative yearly average water scarcity variables including SPEI (Column 1–4) and Precipitation (Column 5–8). CDD is a nonlinear climatic variable for cooling degree days. Other control variables contain installed capacity, electricity price and fixed assets investment. Robust standard errors adjusted for clustering at the power plant-year level are in parentheses. The sample spans 2007 through 2014. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3. Accounting for seasonal changes

Yearly average drought indicators may level off certain information. To accurately reflect the seasonal shocks, we divide the yearly PDSI index into four quarters to study how seasonal water availability affects the generation mix. The results are displayed in Appendix table AT2. Coal-fired and hydro generation are susceptible to seasonal variations over time. The results demonstrate that the water availability in dry (Q1 and Q4) versus the wet seasons (Q2 and Q3) are different. We note that there are clear technology shifts in wet seasons, Q2 (from April to June) and Q3 (from July to September).

The results show that the estimated coefficients of PDSI are positive for hydro technology during the wet season in Q2 within 10% confidential interval while coal power generation are not affected. And the estimated coefficients of PDSI are negative for coal-fired technology during the wet season in Q3 and are statistically significant within 10%. This result indicates that a one-standard-deviation drought induces a decrease in hydro generation by about 195–306 GWh in Q2, which is partially offset by the increase in coal-fired generation of around 33–42 GWh in Q3. The results are similar for SPEI and precipitation. In addition, during dry season in Q1 and Q4, our results indicate that when water availability declines, coal, and hydro electricity generation increase to some extent.

The seasonal fluctuations can be explained by following reasons. Although there is ample water in the wet seasons, the water flows are regulated to support agriculture, the dam usually drains away water during the wet season that occurs in Q2 and Q3 (Tan 2016). During the dry season of Q1 and Q4, hydroelectric generation can increase by adjusting load utilization hours for generators; however, in the wet season in Q2 and Q3, hydroelectric generation decreases due to restricted water resources and flow. Therefore, at these times when water is scarcer, it is necessary to utilize coal-fired generation to meet the demand for electricity. For the dry seasons, the hydro power plants can take advantage of stored water in the dam during the dry season in Q1 (from January to March) and Q4 (from October to December). This is because hydroelectric power stations in the sample are storage hydropower plants and use reservoirs to accumulate water (Gaudard et al., 2018).

5.4. Accounting for nonlinearity

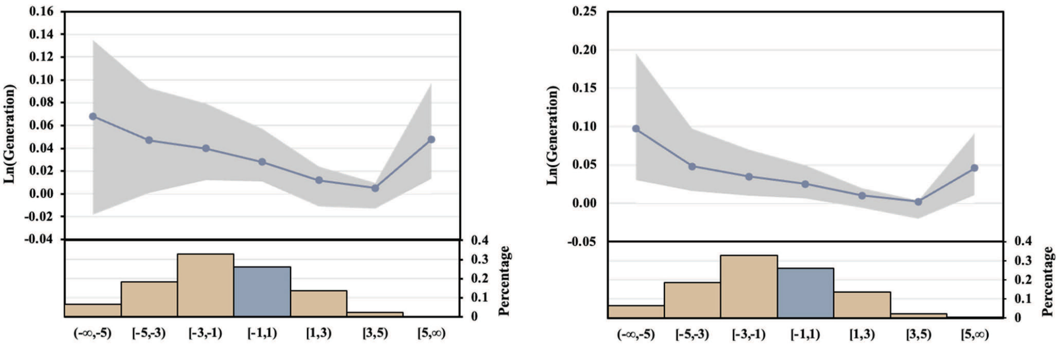
Next, we use the drought severity bins of the PDSI variable to show whether the monthly nonlinear relationship between water scarcity and power generation exists[5]. We estimate Equation (3) and the results are listed in Appendix table AT3.

Figure 3 provides a graphical illustration of the results. Each point in the graphs estimates the marginal effect, that is to say, to what extent an additional month imposing on PDSI a particular bin of water scarcity distribution affects electricity generation. The 95% confidence bands of coefficient estimations of PDSI bins are portrayed by the shaded areas. The horizontal axis is PDSI, while the vertical axis of Figures 2(a) and 2(b) denotes the log electricity generation of the sample plants and the log of coal-fuel type generation, respectively. Moving from left to right, the figures show the water abundance marginal effect from extremely arid conditions to extremely wet conditions. A remarkable finding is that electricity generation responds positively to severe drought or extreme wet. However, the results show most of the coefficients of the water scarcity distribution bins in the arid condition are statistically pronounced, which suggests that, the power generation are more susceptible to the drought condition than the moist condition. The figures demonstrate that the marginal effects of frequency of drought or water abundance imposed by the variations in the water scarcity indicator are increasingly larger, especially at the driest edge of the water abundance spectrum. This

5. Further, we follow Eyer and Wichman (2018) and disaggregate the water scarcity index of PDSI distribution into ($-\infty$, –5), [–5, –2), [–2, 0), [0,2), [2,5), and [5, $+\infty$) six bins. The results are showed in Appendix table AT4 and are similar to that of the seven bins definition.

result indicates that a change from moderate drought to extreme drought will enhance the electricity generation of both the total and coal-fired sectors.

Figure 3: Monthly drought frequency variation effects on generation



(a) PDSI effect on power plant generation

(b) PDSI effect on coal power plant generation

Notes: The blue curve represents point estimation of drought bins. Each point in the graphs estimates the marginal effect, that is to say, to what extent an additional month, imposing on PDSI at particular bin of water scarcity distribution, affects electricity generation. The 95% confidence intervals are the shaded areas. Histograms at the bottom demonstrate the percentage distribution of each water scarcity bin in the sample. The blue histogram displays the near normal water bin.

The results are consistent throughout the distribution of PDSI. Specifically, an additional month at the (–∞, –5) [–5, –3), and [–3, –1) bin can lead to a substantial increase in annual per electricity generation by 17 GWh, 12 GWh, and 10 GWh, respectively, while generation increases by 7 GWh with an additional month falling into the near normal water bins of [–1, 1), holding all else the same.

For coal-fired generation, an additional month in the (–∞, –5), [–5, –3), [–3, –1), and [–1,1) bins, conditioned on a yearly standard deviation for PDSI, results in a power generation increase by around 25 GWh, 12 GWh, 8 GWh, and 6 GWh, respectively. For an additional month in the extreme wet bin of [5,+∞), average power plant and per coal-fired power generation increase by 11 GWh, respectively.

5.5. Placebo tests

One may argue that the estimated technology substitution is driven by newly built generators or regular maintenance. To rule out such possibilities, we have provided additional analyses in Appendix table AT5.

Specifically, we obtain information on the actual completed investment in new electric power construction (NEW) to capture the confounding effects attributed to the newly built generators. This information is obtained from the *Almanac of China's Waterpower* (NBS 2008–2015) and the *Compilation of Statistical Materials of Electric Power Industry* (CEC 2009–2011 & 2014). To rule out the effect of regular maintenance, we construct the variable of service factor (SF). It is one indicator for electricity reliability that considers the lack of availability of active generators due to planned or unplanned outages. The service factor is measured by the ratio of service hours to period hours. The data are obtained from the *Report of National Power Reliability Index* (CEC 2012–2016) and the *Statistics Analysis of National Power Reliability* (Cheng and Zhou 2010). We tabulate both variables by fuel source in the electricity sector.

As shown in Appendix table AT6, we find that the effects of both the newly built generators and maintenance services on the technology mix of electricity generation are insignificant or negligible in magnitude compared to that attributed to water scarcity. Therefore, we have strong evidence that the electricity shortages in China during the period 2007–2014 were mainly driven by water scarcity.

6. FURTHER ANALYSIS

In this section, we re-estimate our model by looking into the characteristics of the electricity generators' cooling technology and the source of water. We also discuss whether there are spatial effects on water stress-induced technology substitution across power grids.

6.1 Effects of generators' water withdrawal characteristics

We examine the effects of water scarcity based on the characteristics of the electricity generators' cooling technology and water sources.

The results are shown in Table 6 and Table 7. In general, increasing water scarcity is correlated with reductions in electricity generation from plants that do not use water for cooling, while droughts result in hydro generation being displaced by increased generation from thermal plants that use nuclear and coal with once-through and recirculating cooling technologies. Moreover, the results indicate that there is no statistically significant generation shift from plants using dry and hybrid cooling technologies. At present, dry-cooled and hybrid-cooled systems are far less prevalent in China than once-through and recirculating systems due to the relatively high operating costs. In

Table 6: Water scarcity effect on the choice of technology for cooling

Dependent variable Ln(generation)	Model _ CT (1)		Model _ CT (2)		Model _ CT (3)		Model _ CT (4)	
PDSI × Once-through	–0.302***	(0.095)	–0.216**	(0.089)	–0.297***	(0.093)	–0.208**	(0.088)
PDSI × Recirculating	–0.185**	(0.083)	–0.188**	(0.093)	–0.194**	(0.087)	–0.196**	(0.097)
PDSI × Other I for coal	0.060	(0.079)	0.061	(0.081)	0.053	(0.077)	0.072	(0.084)
PDSI × Other II for hydro	0.636***	(0.167)	0.772***	(0.174)	0.457*	(0.235)	0.603**	(0.247)
PDSI × Other III for nuclear	–0.999***	(0.366)	–0.768**	(0.366)	–1.364***	(0.427)	–1.156***	(0.398)
CDD	Yes		Yes		Yes		Yes	
Control variables	Yes		Yes		Yes		Yes	
Observations	1800		1800		1800		1800	
No. of coal plants	195		195		195		195	
No. of hydro plants	25		25		25		25	
No. of nuclear plants	5		5		5		5	
Within R-squared	0.114		0.112		0.110		0.106	
Plant fixed effects	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
Power grid × Year fixed effects	No		Yes		No		Yes	
Power plant type × Year fixed effects	No		No		Yes		Yes	

Notes: The table presents results for effects of water scarcity on the choice of technology for cooling. The dependent variable is the logarithm of power generation at the plant level. The key independent variables are interactions between yearly average PDSI and electricity generators' cooling technology. Other I for coal refers to power plants for which adapt dry cooled and hybrid cooled systems. Hydroelectric power plants use no cooling technology and are grouped into the *Other* II subcategory. CDD is a nonlinear climatic variable for cooling degree days. Other control variables contain installed capacity, electricity price and fixed assets investment. Robust standard errors adjusted for clustering at the power plant-year level are in parentheses. The sample spans 2007 through 2014. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Water scarcity effect on technology by water sources

Dependent variable Ln(generation)	Model _ WS (1)		Model _ WS (2)		Model _ WS (3)		Model _ WS (4)	
PDSI × Surface water	–0.237**	(0.118)	–0.223*	(0.124)	–0.221*	(0.116)	–0.194	(0.124)
PDSI × Groundwater	0.366	(0.265)	0.337	(0.263)	0.325	(0.262)	0.292	(0.259)
PDSI × Municipal wastewater	–0.404*	(0.244)	–0.354	(0.252)	–0.415*	(0.247)	–0.383	(0.256)
PDSI × Seawater	–0.129	(0.135)	–0.044	(0.123)	–0.135	(0.139)	–0.060	(0.125)
PDSI × Other	0.166	(0.118)	0.205	(0.125)	0.110	(0.120)	0.167	(0.125)
CDD	Yes		Yes		Yes		Yes	
Control variables	Yes		Yes		Yes		Yes	
Observations	1800		1800		1800		1800	
No. of coal plants	195		195		195		195	
No. of hydro plants	25		25		25		25	
No. of nuclear plants	5		5		5		5	
Within R-squared	0.109		0.106		0.107		0.102	
Plant fixed effects	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
Power grid × Year fixed effects	No		Yes		No		Yes	
Power plant type × Year fixed effects	No		No		Yes		Yes	

Notes: The table presents results for effects of water scarcity on the technology by water sources. The dependent variable is the logarithm of power generation at the plant level. The key independent variables are interactions between yearly average PDSI and electricity generators' water sources. Other water source refers to electricity plants that do not consume or withdraw water or where their water source is not indicated. CDD is a nonlinear climatic variable for cooling degree days. Other control variables contain installed capacity, electricity price and fixed assets investment. Robust standard errors adjusted for clustering at the power plant-year level are in parentheses. The sample spans 2007 through 2014. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the dataset used for the study, hydroelectric power plants use no cooling technology and are grouped into the *Other II* subcategory. A one-standard-deviation increase in water scarcity results in a reduction in hydroelectricity generation by 206 GWh per plant and an increase in nuclear generation by 147 GWh and an increase in coal-fired generation that uses once-through and recirculating cooling systems by 61 GWh and 39 GWh, respectively.

In terms of water sources, increased water shortages can trigger an increase in electricity generation from power plants that use surface water or municipal wastewater. A one-standard-deviation decrease in PDSI results in a 49 GWh and 77 GWh increase in generation from surface water-based or municipal wastewater-based plants, respectively. This situation may be due to the decision makers recognising that surface water or municipal wastewater are more reliable sources of water for cooling than other fluctuating levels of fresh water. As seawater is abundant, generation by nuclear plants that draw seawater for cooling is less affected by the water shortages. This finding corresponds to our previous result that showed an increase in nuclear generation during periods of water shortage.

The impact of groundwater is not significant. In fact, groundwater has been strictly controlled for power plant withdrawal in northern China, in particular in the regions with water shortages. The central government also prohibits the use of groundwater for newly constructed or expanded power stations. More importantly, the central government encourages power plants to utilize the wastewater from municipal sewage treatment plants for cooling purposes (National Bureau of Statistics of China 2004). Our result with regard to the increased use of municipal wastewater confirms such actions enacted by the government.

We then drop hydro plants and construct a sub-sample applying cooling technologies to investigate how generation is allocated across coal and nuclear. The results displayed in Appendix

Table AT6 indicate that droughts cause increase in power generation for nuclear and coal using one-through and recirculating cooling technologies. It is consistent with full sample results. We also show how electricity generation allocation is dependent on the water sources. Appendix Table AT7 indicates power plants that withdraw fresh water are sensitive to water. We find that reduction in water availability triggers an increase in electricity generation for power plants that use surface water and a reduction in power generation for plants using groundwater.

We then drop hydro plants and construct a sub-sample applying cooling technologies to investigate how generation is allocated across coal and nuclear. The results displayed in Appendix Table AT6 indicate that droughts cause increase in power generation for nuclear and coal using one-through and recirculating cooling technologies. It is consistent with full sample results. We also show how electricity generation allocation is dependent on the water sources. Appendix Table AT7 indicates power plants that withdraw fresh water are sensitive to water. We find that reduction in water availability triggers an increase in electricity generation for power plants that use surface water and a reduction in power generation for plants using groundwater.

Power sector in China is a relative monopoly industry. Five generation corporations own a large share of the national generation capacity. They decide the generation technologies based on factors such as local water availability, hydrological conditions as well as technical and economic considerations when constructing, re-building or expanding generators. Plants themselves therefore cannot switch cooling technologies after putting into use.

6.2 Spatial effects of water scarcity on inter-grid transmission

We have shown that water scarcity in one region induces technology substitution in the same region. Next, we discuss whether there is a spatial effect across regions through the inter-grid transmission. If the power grids are well connected and free to transmit without barriers, we would expect that water scarcity in one grid region could induce technology substitution in other grid regions.

We construct water scarcity indices for the six power grids by calculating the average value of PDSI for each of the six grid regions. To verify the existence of a spatial effect, in addition to our original model specification, the new indices are interacted with the technology variables in the other five grid regions. We first test whether the water scarcity in the region where the Southern Power Grid Corporation (SPGC) is located affects the technology mix in the region where the State Grid Corporation is located. The results are shown in column 1 of Table 8. The technology substitution within the SPGC region remains, which is consistent with our main findings. The estimated coefficients for the new interaction terms are all insignificant, which suggests that water scarcity in the SPGC region has no spatial effects on the technology substitution for State Grid Corporation, implying that the inter-grid transmission is negligible. Thus, it would appear that the current dispatch system is not sufficiently flexible to accommodate the induced water shortages in one region by utilizing the technology from other regions. Furthermore, we also find that within the five grid regions that are under the control of the State Grid Corporation, technology substitution and thus inter-grid transmission are limited. This is evidenced by the statistically insignificant effects of the interaction terms between the water scarcity of one grid and the technology variables in the other four grid regions within the State Grid Corporation. Therefore, we conclude that there is no spatial effect via inter-grid transmission.

The results imply the inefficiency of the dispatch and transmission system in China power grid network to certain extent, if not completely. The lack of a nationwide barrier-free, inter-grid,

Table 8: Spillover effects of water scarcity on inter-grid transmission

Dependent variable Ln(generation)	Model_ SPG (1)	(2)	Model_ NPG (3)	(4)	Model_ EPG (5)	(6)
PDSI× Coal	–0.119*	–0.109	–0.219**	–0.226**	–0.224**	–0.211**
	(0.069)	(0.074)	(0.091)	(0.101)	(0.087)	(0.103)
PDSI× Hydro	0.636**	0.713*	0.929*	1.239**	0.872*	1.010*
	(0.293)	(0.371)	(0.474)	(0.534)	(0.488)	(0.537)
PDSI× Nuclear	–1.036***	–1.064**	–1.278***	–1.311***	–1.403***	–1.300***
	(0.329)	(0.418)	(0.403)	(0.498)	(0.499)	(0.500)
$PDSI_{SPGC}$× Coal	0.181	0.388				
	(0.436)	(0.746)				
$PDSI_{SPGC}$× Hydro	1.362	2.013				
	(1.255)	(2.511)				
$PDSI_{SPGC}$× Nuclear	0.448	0.000				
	(0.609)	(0.000)				
$PDSI_{NPG}$× Coal			0.110	–6.293		
			(0.354)	(6.301)		
$PDSI_{NPG}$× Hydro			0.293	0.000		
			(0.517)	(0.000)		
$PDSI_{NPG}$× Nuclear			1.284**	0.000		
			(0.585)	(0.000)		
$PDSI_{EPG}$× Coal					–0.043	–0.705
					(0.282)	(1.817)
$PDSI_{EPG}$× Hydro					1.074	0.000
					(1.117)	(0.000)
$PDSI_{EPG}$× Nuclear					0.000	0.000
					(0.000)	(0.000)
CDD	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1800	1800	1472	1472	1472	1472
Number of Coal plants	195	195	165	165	165	165
Number of Hydro plants	25	25	16	16	16	16
Number of Nuclear plants	5	5	3	3	3	3
Within R-squared	0.115	0.105	0.128	0.130	0.130	0.119
Plant fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Power grid × Year fixed effects	No	Yes	No	Yes	No	Yes
Power plant type × Year fixed effects	No	Yes	No	Yes	No	Yes

(continued)

generation dispatch and transmission system could intensify the negative impact of water stress-induced power shortages.

Dispatching in China follows the administrative fair dispatch rule rather than a merit order. Fair dispatch rule overlooks the incentives for plants to be efficient. Dispatch centers are affiliated to the grid companies with multi-level hierarchy. Grid companies act as a single transmission and distribution system operator, and thus have negative effects on system efficiency. Before 2015, the cross-regional (interprovincial or interregional) mid- and long-term trading in China contributed approximately 2% to 10% of the total power transactions. The sellers and buyers were selected administratively. Such contracting was intended to make provincial grids more resilient and improve efficiency of the power system. However, most of the cross-regional power trading was dominated by government. For instance, coal power transmission is required to trade from the Northwest region to the Central or Northern regions and hydropower transmission is required to trade from the Central to the Southern region following a national strategy.

The authority increasingly realized that cross-regional would benefit the whole system efficiency. However, the barriers for resistance from provincial governments because of institutional

Table 8: Spillover effects of water scarcity on inter-grid transmission *(continued)*

Dependent variable	**Model_ NEPG**		**Model_ NWPG**		**Model_ CPG**	
Ln(generation)	(7)	(8)	(9)	(10)	(11)	(12)
PDSI× Coal	–0.243***	–0.173*	–0.232***	–0.217**	–0.226***	–0.211**
	(0.091)	(0.105)	(0.085)	(0.104)	(0.085)	(0.103)
PDSI× Hydro	0.729	0.746	0.895*	1.037*	0.816	0.969*
	(0.493)	(0.549)	(0.480)	(0.534)	(0.530)	(0.540)
PDSI× Nuclear	–1.168**	–1.299***	–1.478***	–1.300***	–1.698***	–1.301***
	(0.504)	(0.499)	(0.473)	(0.500)	(0.490)	(0.500)
$PDSI_{NEPG}$× Coal	0.137	2.933***				
	(0.189)	(0.939)				
$PDSI_{NEPG}$× Hydro	–0.677	0.000				
	(0.583)	(0.000)				
$PDSI_{NEPG}$× Nuclear	0.422	0.000				
	(0.280)	(0.000)				
$PDSI_{NWPG}$ × Coal			–0.364	–0.791		
			(0.469)	(0.651)		
$PDSI_{NWPG}$× Hydro			0.347	0.051		
			(1.483)	(1.553)		
$PDSI_{NWPG}$× Nuclear			0.3	0.000		
			(0.706)	(0.000)		
$PDSI_{CPG}$× Coal					0.436	–1.071
					(0.608)	(3.732)
$PDSI_{CPG}$× Hydro					3.227	0.000
					(3.153)	(0.000)
$PDSI_{CPG}$× Nuclear					1.632	0.000
					(1.513)	(0.000)
CDD	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1472	1472	1472	1472	1472	1472
Number of Coal plants	165	165	165	165	165	165
Number of Hydro plants	16	16	16	16	16	16
Number of Nuclear plants	3	3	3	3	3	3
Within R-squared	0.136	0.125	0.128	0.120	0.130	0.119
Plant fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Power grid × Year fixed effects	No	Yes	No	Yes	No	Yes
Power plant type × Year fixed effects	No	Yes	No	Yes	No	Yes

Notes: The table presents the spillover effects of water scarcity on inter-grid transmission. The dependent variable is the logarithm of generation at the plant level. SPGC represents the Southern Power Grid Corperation. NPG represents the north China power grid. EPG represents the east China power grid. NEPG represents the northeast power grid. NWPG represents the northwest power grid. CPG represents the central China power grid. NPG, NEPG, NWPG, EPG and CPG belong to State Grid Corporation of China. SPG belongs to South Power Grid Company Limited. We construct water scarcity indices for the six power grids by calculating the average value of PDSI for each of the six grid regions. To verify the existence of a spatial effect, in addition to our original model specification, the new indices are interacted with the technology variables in the other five grid regions. CDD is a nonlinear climatic variable for cooling degree days. Other control variables contain installed capacity, electricity price and fixed assets investment. Robust standard errors are in parentheses. The sample spans 2007 through 2014. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

interests make the interregional trading difficult (IEA, 2019). Although Grimm et al. (2022) find it may not be always efficient to minimize redispatch cost in the case of market-based redispatch compared to the cost-based one, the lessons learnt from China's electricity reform suggest that without a market-based pricing system, more efficient system operation and power shortage mitigation could be hard to achieve.

7. ENVIRONMENTAL COSTS

We further investigate the environmental impact of water scarcity by estimating the main result. Based on process chain analysis and life cycle analysis methods, Jiang (2015) calculates greenhouse gas emissions from nuclear power chain life cycle is 6.2–11.9g•CO2/kWh in China. The coal power and hydro-electric chain life cycle emit 1072.4g•CO2/kWh and 0.81–12.8g•CO2/kWh, respectively. This implies, as a result of water induced technology substitution, a one-standard-deviation reduction in PDSI would raise plant-level CO2 emissions by 32000 tons annually. With an average price for carbon emission being 5.50 USD per ton during 2013–2015 in China (Slater 2019), the extra cost for each thermal power plant to emit additional CO2 is equivalent to 0.18 million USD per year. This monetary value could be much higher considering the substantially increased carbon price in China recently. In year 2021, carbon price has reached to the highest level of US$ 13.7 per ton, which implies the environmental cost could increase to 0.44 million USD.

Furthermore, we provide a precise estimation of how frequency of drought severity or water abundance affects CO2 emissions at plant level. By examining CO2 emissions based on nonlinearity results, it shows that an additional month in the (-∞, –5), [–5, –3), [–3, –1), [–1, 1), [1, 3), [3, 5) and [5,∞) bins can lead to an increase in annual average CO2 emissions from each coal power plant by roughly 27064 tons, 12632 tons, 9071 tons, 6404 tons, 2517 tons, 499 tons and 12078 tons, respectively. In the extreme case, the impact of one additional month in the most severe water shortage bin will increase the cost up to 0.15 million USD per plant per year. In the arid period, coal-fired power plants can barely meet the needs of cooling by drawing water. In such situations, the coal-fired plants tend to adopt dry or hybrid cooling systems that require less or no water for cooling (Rodriguez et al. 2013). Therefore, in dry periods, carbon emissions are higher compared to the ample water period.

8. CONCLUSION

This paper answers how utility plants choose technologies for electricity generation in response to the changing water availability. We find power plants replace hydroelectricity by coal-fired generation and nuclear power, which results in unexpected additional use of coal and an increase in carbon emissions. When taking into account the characteristics of water cooling for generators, we find drought leads to a transition in technology from hydroelectric power plants to plants that use once-through and recirculating cooling technologies. In terms of water sources, we find evidence that severe water shortages can trigger increasing electricity generation from power stations that use surface water or municipal wastewater.

In addition, we have introduced the water availability bins to address the monthly nonlinear relationship between the severity of water scarcity (abundance) and power generation. The result indicates that a change from moderate drought to extreme drought will encourage electricity generation from coal-fired plants, as coal-powered technology is less water-intensive than hydro-powered technology. When water availability is at very low levels, hydro or nuclear power are unable to provide the rapid ramping services required to address the demand for electricity.

More specifically, in this paper, we have provided an explanation for the persistent electricity shortages that have been experienced in China in early 2000s. Our analysis shows clearly that the reduction in hydroelectric generation induced by water scarcity cannot be fully offset by thermal power generation. This scenario suggests that water resource constraints have a pronounced negative effect on electricity supply in China. We also recognize that coal-fired power and hydroelectricity are susceptible to seasonal trends over time, with clear technology shifts in the second and third quarter of a year. As the decrease in hydroelectric generation can only be partially offset by coal-fired plants, water scarcity may result in electricity shortages in the second and third quarter of a year in particular. By looking into the spatial effects of water scarcity, we find water scarcity-induced power shortages cannot be compensated for by electricity supply from other regions via inter-grid transmission. This situation may also provide indirect evidence of the inefficiency of the current power dispatch and transmission system.

The environmental implications of water scarcity on carbon-intensive coal generation appears to be increasing. We find CO_2 emissions are increasing in association with the rising use of coal as a fuel source for electricity generation. We also note that a change from moderate drought to extreme drought will largely increase CO_2 emissions. In the arid period, coal-fired power plants cannot withdraw sufficient water to meet the needs of cooling. Therefore, the coal-fired electricity sector is likely to adopt dry or hybrid cooled systems that require less or no water for cooling. In this circumstance, the coal-fired power plants will have relatively higher CO_2 emissions compared to periods when ample water is available. The estimated average carbon emissions increase attributed to water scarcity-induced technology substitution for plant-level is up to 32000 tons per year, resulting in an additional cost of 0.18 million USD. Our findings offer new insights to assist with the adaptation to the decline in water availability in the Chinese power sector. Future policy makers should consider the potential negative impact of drought and the constraints of water resources on the level of CO_2 emissions.

Our results for policy implications is subject to several major caveats. First, our work is a novel approach to the relationship between water scarcity and the selection of electricity technology. However, as the power sector is a state-controlled industry and our dataset incorporates only observations of power plants with installed capacity of over one gigawatt that are affiliated with the five giant generation corporations, and the precise information on the switching cost from one technology to another is missing. The induced technology selection is more a reflection of government decision than reaction by individual plants. What we estimate is thus an average effect of government response to drought rather than the market effect of individual generators. Another caveat is that technologies based on renewable sources are absent in our analysis. In addition, long-run water availability can affect the construction of new power plants and thus shift the construction selection for differently fuelled power plants. In our study, we have not taken such effects into consideration.

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REFERENCES

Allcott, H., A. Collard-Wexler, and S.D. O'Connell (2016). "How do electricity shortages affect industry? Evidence from India." *American Economic Review* 106(3): 587–624. https://doi.org/10.1257/aer.20140389.

Alley, W. (1984). "The Palmer Drought Severity Index: limitations and assumptions." *Journal of Applied Meteorology and Climatology* 23(7): 1100–9. https://doi.org/10.1175/1520-0450(1984)023<1100:TPDSIL>2.0.CO;2.

Amor, M.B., E.B. de Villemeur, M. Pellat, and P.O. Pineau (2014). "Influence of wind power on hourly electricity prices and GHG (greenhouse gas) emissions: Evidence that congestion matters from Ontario zonal data." *Energy* 66: 458–469. https://doi.org/10.1016/j.energy.2014.01.059.

Archsmith, J. (2020). "Dam Spillovers: The direct and indirect costs from environmental constraints on hydroelectric generation." Available at SSRN 3046246.

Auffhammer, M. and A. Aroonruengsawat (2011). "Simulating the impacts of climate change, prices and population on California's residential electricity consumption." *Climatic Change* 109(1): 191–210. https://doi.org/10.1007/s10584-011-0299-y.

Bai, J. (2009). "Panel data models with interactive fixed effects." *Econometrica* 77(4): 1229–1279. https://doi.org/10.3982/ECTA6135.

Barreca, A., K. Clay, O. Deschenes, M. Greenstone, and J.S. Shapiro (2016). "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century." *Journal of Political Economy* 124(1): 105–159. https://doi.org/10.1086/684582.

Behrens, P., M.T. Van Vliet, T. Nanninga, B. Walsh, and J.F. Rodrigues (2017). "Climate change and the vulnerability of electricity generation to water stress in the European Union." *Nature Energy* 2(8): 1–7. https://doi.org/10.1038/nenergy.2017.114.

Boomhower, J. and L. Davis (2020). "Do energy efficiency investments deliver at the right time?" *American Economic Journal: Applied Economics* 12(1): 115–39. https://doi.org/10.1257/app.20170505.

Bretschger, L. and L. Zhang (2017). "Carbon policy in a high-growth economy: The case of China." *Resource and Energy Economics* 47: 1–19. https://doi.org/10.1016/j.reseneeco.2016.10.001.

Cameron, A.C. and D.L. Miller (2015). "A practitioner's guide to cluster-robust inference." *Journal of Human Resources* 50(2): 317–372. https://doi.org/10.3368/jhr.50.2.317.

Chen, X. and L. Yang (2019). "Temperature and industrial output: Firm-level evidence from China." *Journal of Environmental Economics and Management* 95: 257–274. https://doi.org/10.1016/j.jeem.2017.07.009.

Cheng, X. and H. Zhou (2010). "Statistics analysis of national power reliability in 2009." *Electric Power* (9): 29–36.

China Electricity Council (CEC) (2009–2011 & 2014). Compilation of statistical materials of electric power industry 2009–2011 & 2014. Beijing.

China Electricity Council (CEC) (2012). The national picture of electricity supply-demand in 2011 and analytical forecast in 2012. http://www.cec.org.cn/guihuayutongji/gongxufenxi/dianligongxufenxi/2012-02-03/79721.html.

China Electricity Council (CEC) (2012–2016). Report of national power reliability index 2012–2016. Beijing.

China Electricity Council (CEC) (2013). Materials of national energy efficiency benchmarking competition for thermal power units 2012. Beijing.

Clancy, J.M., F. Gaffney, J.P. Deane, J. Curtis, and B.Ó. Gallachóir (2015). "Fossil fuel and CO2 emissions savings on a high renewable electricity system-a single year case study for Ireland." *Energy Policy* 83: 151–164. https://doi.org/10.1016/j.enpol.2015.04.011.

Couttenier, M. and R. Soubeyran (2014). "Drought and civil war in sub-saharan africa." *The Economic Journal* 124(575): 201–244. https://doi.org/10.1111/ecoj.12042.

Craig, M.T., I.L. Carreño, M. Rossol, B.M. Hodge, and C. Brancucci (2019). "Effects on power system operations of potential changes in wind and solar generation potential under climate change." *Environmental Research Letters* 14(3): 034014. https://doi.org/10.1088/1748-9326/aaf93b.

Dai, A. and National Center for Atmospheric Research Staff (Eds) (2019). "The climate data guide: Palmer Drought Severity Index (PDSI)." Accessed December 12, https://climatedataguide.ucar.edu/climate-data/palmer-drought-severity-index-pdsi.

Dai, A. (2011a). "Characteristics and trends in various forms of the Palmer Drought Severity Index during 1900–2008." *Journal of Geophysical Research: Atmospheres* 116(D12). https://doi.org/10.1029/2010JD015541.

Dai, A. (2011b). "Drought under global warming: a review." *Wiley Interdisciplinary Reviews: Climate Change* 2(1): 45–65. https://doi.org/10.1002/wcc.81.

Dai, A. (2017). Dai Global Palmer Drought Severity Index (PDSI). Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory. Accessed April 05, 2019, https://doi.org/10.5065/D6QF8R93.

Debaere, P. (2014). "The global economics of water: Is water a source of comparative advantage?" *American Economic Journal: Applied Economics* 6(2): 32–48. https://doi.org/10.1257/app.6.2.32.

DeNooyer, T.A., J.M. Peschel, Z. Zhang, and A.S. Stillwell (2016). "Integrating water resources and power generation: The energy-water nexus in Illinois." *Applied Energy* 162: 363–371. https://doi.org/10.1016/j.apenergy.2015.10.071.

Eyer, J. and C.J. Wichman (2018). "Does water scarcity shift the electricity generation mix toward fossil fuels? Empirical evidence from the United States." *Journal of Environmental Economics and Management* 87: 224–241. https://doi.org/10.1016/j.jeem.2017.07.002.

Feeley III, T.J., T.J. Skone, G.J. Stiegel Jr, A. McNemar, M. Nemeth, B. Schimmoller, J.T. Murphy, and L. Manfredo (2008). "Water: A critical resource in the thermoelectric power industry." *Energy* 33(1): 1–11. https://doi.org/10.1016/j.energy.2007.08.007.

Fisher-Vanden, K., E.T. Mansur, and Q.J. Wang (2015). "Electricity shortages and firm productivity: Evidence from China's industrial firms." *Journal of Development Economics* 114: 172–188. https://doi.org/10.1016/j.jdeveco.2015.01.002.

Gao, X., Y. Zhao, S. Lu, Q. Chen, T. An, X. Han, and L. Zhuo (2019). "Impact of coal power production on sustainable water resources management in the coal-fired power energy bases of Northern China." *Applied Energy* 250: 821–833. https://doi.org/10.1016/j.apenergy.2019.05.046.

Gaudard, L., F. Avanzi, and C. De Michele (2018). "Seasonal aspects of the energy-water nexus: The case of a run-of-the-river hydropower plant." *Applied Energy* 210: 604–612. https://doi.org/10.1016/j.apenergy.2017.02.003.

Grimm, V., A. Martin, C. Sölch, M. Weibelzahl, and G. Zöttl, (2022). "Market-based redispatch may result in inefficient dispatch." *The Energy Journal* 43(5). https://doi.org/10.5547/01956574.43.5.csol.

Gu, F. and Y. Xiao (2018). "Reform and outlook for the management systems of electricity generation and utilization plan over past forty years." http://news.bjx.com.cn/html/20181010/932803.shtml (in Chinese).

Hart, R. (2004). "Growth, environment and innovation-a model with production vintages and environmentally oriented research." *Journal of Environmental Economics and Management* 48(3): 1078–1098. https://doi.org/10.1016/j.jeem.2004.02.001.

IEA (2019). *China Power System Transformation: Assessing the benefit of optimized operations and advanced flexibility options*. OECD Publishing, Paris, https://doi.org/10.1787/22655cc0-en. https://doi.org/10.1787/22655cc0-en.

Jacobsen, H.K., and S.T Schröder (2012). "Curtailment of renewable generation: Economic optimality and incentives." *Energy Policy* 49: 663–675. https://doi.org/10.1016/j.enpol.2012.07.004.

Jiang, Z., Z. Pan, J. Xing, and F. Yu (2015). "Greenhouse gas emissions from nuclear power chain life cycle in China." *China Environmental Science* 35(11): 3502–3510.

Kahrl, F., J.H. Williams, and J. Hu (2013). "The political economy of electricity dispatch reform in China." *Energy Policy* 53: 361–369. https://doi.org/10.1016/j.enpol.2012.10.062.

Khan, Z., P. Linares, and J. García-González (2016). "Adaptation to climate-induced regional water constraints in the Spanish energy sector: An integrated assessment." *Energy Policy* 97: 123–135. https://doi.org/10.1016/j.enpol.2016.06.046.

Levi, M.D. and B.R. Nault (2004). "Converting technology to mitigate environmental damage." *Management Science* 50(8): 1015–1030. https://doi.org/10.1287/mnsc.1040.0238.

Li, Y., W. A. Pizer, and L.Wu (2019). "Climate change and residential electricity consumption in the Yangtze River Delta, China." *Proceedings of the National Academy of Sciences* 116(2): 472–477. https://doi.org/10.1073/pnas.1804667115.

Lin, B. and X. Liu (2013). "Electricity tariff reform and rebound effect of residential electricity consumption in China." *Energy* 59: 240–247. https://doi.org/10.1016/j.energy.2013.07.021.

Meldrum, J., S. Nettles-Anderson, G. Heath, and J. Jordan Macknick (2013). "Life cycle water use for electricity generation: A review and harmonization of literature estimates." *Environmental Research Letters* 8(1): 015031. https://doi.org/10.1088/1748-9326/8/1/015031.

Mendelsohn, R., W.D. Nordhaus, and D. Shaw (1994). "The impact of global warming on agriculture: A Ricardian analysis." *American Economic Review* 753–771.

Miara, A., J.E. Macknick, C.J. Vörösmarty, V.C. Tidwell, R. Newmark, and B. Fekete (2017). "Climate and water resource change impacts and adaptation potential for US power supply." *Nature Climate Change* 7(11): 793. https://doi.org/10.1038/nclimate3417.

Milly, P.C., K.A. Dunne, and A.V. Vecchia (2005). "Global pattern of trends in streamflow and water availability in a changing climate." *Nature* 438(7066): 347–350. https://doi.org/10.1038/nature04312.

Misiolek, W.S. (1980). "Effluent taxation in monopoly markets." *Journal of Environmental Economics and Management* 7(2): 103–107. https://doi.org/10.1016/0095-0696(80)90012-1.

Moomaw, W., P. Burgherr, G. Heath, M. Lenzen, J. Nyboer, and A. Verbruggen (2011). *Annex II: Methodology. In IPCC special report on renewable energy sources and climate change mitigation*. United Kingdom, Cambridge: Cambridge University Press.

Morales-España, G., E. Nycander, and J. Sijm (2021). "Reducing CO2 emissions by curtailing renewables: Examples from optimal power system operation." *Energy Economics* 99: 105277. https://doi.org/10.1016/j.eneco.2021.105277.

National Bureau of Statistics of China (2008–2015). Almanac of China's waterpower 2008–2015 Beijing: China Statistics Press.

National Bureau of Statistics of China (2008–2015). China electric power yearbook 2008–2015 Beijing: China Statistics Press.

National Oceanic and Atmospheric Administration. Terrestrial air temperature and precipitation. Accessed March 20, 2019, https://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html#detail.

Olmstead, S.M. (2010). "The economics of managing scarce water resources." *Review of Environmental Economics and Policy* 4(2): 179–198. https://doi.org/10.1093/reep/req004.

Olmstead, S.M. (2014). "Climate change adaptation and water resource management: A review of the literature." *Energy Economics* 46: 500–509. https://doi.org/10.1016/j.eneco.2013.09.005.

Qiu, L.D., M. Zhou, and X. Wei (2018). "Regulation, innovation, and firm selection: The porter hypothesis under monopolistic competition." *Journal of Environmental Economics and Management* 92: 638–658. https://doi.org/10.1016/j.jeem.2017.08.012.

Research Council UK. China emission accounts and datasets (CEADs). Accessed April 10, 2019, http://www.ceads.net/data/inventory-by-sectoral-approach/.

Rodriguez, D.J., A. Delgado, A. DeLaquil and A. Sohns (2013). *Thirsty energy*. Information, Communication and Technology (ICT) Department, Water Partnership Program. Washington, DC.

Rübbelke, D. and S. Vögele (2011). "Impacts of climate change on European critical infrastructures: The case of the power sector." *Environmental Science and Policy* 14(1): 53–63. https://doi.org/10.1016/j.envsci.2010.10.007.

Slater, H. (2019). "How China's rising carbon price impacts the market." https://www.icf.com/insights/public-policy/china-carbon-price.

State Electricity Regulation Commission. (2008–2015). Electricity pricing supervision report 2008–2015 (in Chinese). State Electricity Regulatory Commission PR China, Beijing.

State Electricity Regulatory Commission. (2011). Electricity regulatory annual report 2010 (in Chinese). State Electricity Regulatory Commission PR China, Beijing.

Stewart, M.B. (1980). "Monopoly and the intertemporal production of a durable extractable resource." *Quarterly Journal of Economics* 94(1): 99–111. https://doi.org/10.2307/1884606.

Sun, C. and B. Lin (2013). "Reforming residential electricity tariff in China: Block tariffs pricing approach." *Energy Policy* 60: 741–752. https://doi.org/10.1016/j.enpol.2013.05.023.

Tan, Y. (2016). *Investigation on hydropower stations along the Yangtze River: Hydropower generators almost at full capacity*. Futures Daily, July 1.

Van Vliet, M.T.H., J.R. Yearsley, F. Ludwig, S. Vögele, D.P. Lettenmaier, and P. Kabat (2012). "Vulnerability of US and European electricity supply to climate change." *Nature Climate Change* 2(9): 676. https://doi.org/10.1038/nclimate1546.

Vicente-Serrano S.M. and National Center for Atmospheric Research Staff. (Eds). (2015). The climate data guide: Standardized Precipitation Evapotranspiration Index (SPEI). https://climatedataguide.ucar.edu/climate-data/standardized-precipitation-evapotranspiration-index-spei.

Wang, C., R. Wang, E. Hertwich, Y. Liu, and F. Tong (2019). "Water scarcity risks mitigated or aggravated by the inter-regional electricity transmission across China." *Applied Energy* 238: 413–422. https://doi.org/10.1016/j.apenergy.2019.01.120.

Wang, Q. and X. Chen (2012). "China's electricity market-oriented reform: From an absolute to a relative monopoly." *Energy Policy* 51: 143–148. https://doi.org/10.1016/j.enpol.2012.08.039.

World Nuclear Association. 2020. Nuclear power in China. https://www.world-nuclear.org/information-library/country-profiles/countries-a-f/china-nuclear-power.aspx.

Wu, Y. (2009). China's capital stock series by region and sector. PhD diss., Business School, Economics, University of Western Australia.

Xie, Y. and D. Zilberman (2018). "Water storage capacity versus water use efficiency: Substitutes or complements?" *Journal of the Association of Environmental and Resource Economists* 5(1): 265–299. https://doi.org/10.1086/694178.

Yue, H. (2021). "The logic behind the "electricity shortage" in China: From the relation between three pairs of cycles." https://news.bjx.com.cn/html/20211008/1180325.shtml.

Zhang, C., J. Li (2020). "Assessment on the water efficiency of coal-fired power generating units in China and the effect of strengthening water withdrawal quotas." Technical Report for Donation Program of Energy Foundation, G-1906-29810.

Zhang, C., L. Zhong, X. Fu, and Z. Zhao (2016). "Managing scarce water resources in China's coal power industry." *Environmental management* 57(6), 1188–1203. https://doi.org/10.1007/s00267-016-0678-2.

Zhang, C., L. Zhong, S. Liang, K.T. Sanders, J. Wang, and M. Xu (2017). "Virtual scarce water embodied in inter-provincial electricity transmission in China." *Applied Energy* 187: 438–448. https://doi.org/10.1016/j.apenergy.2016.11.052.

Zhang, C., L. Zhong, X. Fu, J. Wang, and Z. Wu (2016). "Revealing water stress by the thermal power industry in China based on a high spatial resolution water withdrawal and consumption inventory." *Environmental Science and Technology* 50(4): 1642–1652. https://doi.org/10.1021/acs.est.5b05374.

Zheng, X., C. Wang, W. Cai, M. Kummu, and O. Varis (2016). "The vulnerability of thermoelectric power generation to water scarcity in China: Current status and future scenarios for power planning and climate change." *Applied Energy* 171: 444–455. https://doi.org/10.1016/j.apenergy.2016.03.040.

Zhou, Y., M. Ma, P. Gao, O. Xu, J. Bi, and T. Naren (2019). "Managing water resources from the energy-water nexus perspective under a changing climate: A case study of Jiangsu province, China." *Energy Policy* 126: 380–390. https://doi.org/10.1016/j.enpol.2018.11.035.

APPENDIX

AT1: Water cooling technology, water sources and fuel source distribution

Water cooling technology:		Water Sources:		Percentage of total generation (No. of power plants)	
Once-through	30%	Surface water	35%	Coal power plant	87% (195)
Recirculating	30%	Groundwater	10%	Hydroelectric power plant	11% (25)
Other I for coal[1]	31%	Municipal wastewater	8%	Nuclear power plant	2% (5)
Other II for hydro[2]	11%	Seawater	18%		
Other III for nuclear	2%	Other[3]	40%		

[1]Other I for coal refers to power plants for which adapt dry cooled and hybrid cooled systems. [2] Other II for hydro refers to plants where no cooling type is released. [3]Other water source refers to electricity plants that do not consume or withdraw water or where their water source is not indicated. *Source:* Authors' calculation based on China Electric Power Yearbook and China Electricity Council (CEC).

AT2: Seasonal variation effects of water scarcity

Dependent variable Ln(generation)	Model _ PDSI				Model _ SPEI				Model _ Precipitation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Water scarcity indicator (Q1) × Coal	–0.077	–0.030	–0.121	–0.079	–0.187***	–0.201*	–0.171**	–0.163	–0.003**	–0.004*	–0.003*	–0.003
	(0.088)	(0.119)	(0.099)	(0.125)	(0.063)	(0.112)	(0.071)	(0.123)	(0.001)	(0.002)	(0.002)	(0.003)
Water scarcity indicator (Q1) × Hydro	–0.248	–0.169	–0.441*	–0.387	–0.189	–0.103	–0.502*	–0.396	–0.007	–0.007	–0.010	–0.009
	(0.189)	(0.203)	(0.235)	(0.254)	(0.176)	(0.171)	(0.292)	(0.276)	(0.007)	(0.008)	(0.006)	(0.006)
Water scarcity indicator (Q2) ×Coal	0.124	0.092	0.175	0.144	0.021	–0.049	0.027	–0.050	0.000	0.001	0.000	0.001
	(0.102)	(0.114)	(0.119)	(0.128)	(0.047)	(0.058)	(0.049)	(0.060)	(0.001)	(0.001)	(0.001)	(0.001)
Water scarcity indicator (Q2) × Hydro	0.626**	0.609*	0.795**	0.841**	0.440	0.356	0.663***	0.536***	0.008***	0.008***	0.008***	0.009***
	(0.315)	(0.320)	(0.387)	(0.389)	(0.300)	(0.303)	(0.189)	(0.189)	(0.003)	(0.003)	(0.002)	(0.002)
Water scarcity indicator (Q3) × Coal	–0.154**	–0.197**	–0.165**	–0.201**	–0.072	–0.056	–0.058	–0.033	–0.001**	–0.001*	–0.001**	–0.001*
	(0.068)	(0.082)	(0.068)	(0.087)	(0.054)	(0.051)	(0.054)	(0.057)	(0.000)	(0.001)	(0.001)	(0.001)
Water scarcity indicator (Q3) × Hydro	0.144	0.091	0.036	–0.041	0.347**	0.376**	0.174	0.165	0.004	0.004	0.003	0.003
	(0.330)	(0.346)	(0.332)	(0.324)	(0.162)	(0.159)	(0.197)	(0.204)	(0.004)	(0.005)	(0.005)	(0.006)
Water scarcity indicator (Q4) × Coal	–0.007	0.053	–0.015	0.050	–0.081**	–0.074	–0.088**	–0.080	–0.001	0.000	–0.001	–0.000
	(0.054)	(0.073)	(0.055)	(0.084)	(0.036)	(0.055)	(0.037)	(0.054)	(0.001)	(0.001)	(0.001)	(0.001)
Water scarcity indicator (Q4) × Hydro	–0.001	0.140	–0.073	0.059	–0.374**	–0.345**	–0.184	–0.149	–0.011***	–0.008**	–0.008**	–0.005
	(0.313)	(0.332)	(0.300)	(0.310)	(0.145)	(0.147)	(0.164)	(0.147)	(0.003)	(0.004)	(0.003)	(0.003)
CDD	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1800	1800	1800	1800	1800	1800	1800	1800	1800	1800	1800	1800
No. of coal plants	195	195	195	195	195	195	195	195	195	195	195	195
No. of hydro plants	25	25	25	25	25	25	25	25	25	25	25	25
Within R-squared	0.112	0.109	0.109	0.103	0.117	0.111	0.115	0.104	0.124	0.119	0.120	0.112
Plant fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Power grid ×Year fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Power plant type × Year fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes

Notes: The table presents results for seasonal variation effects of water shortage. The dependent variable is the logarithm of generation at the plant level. The key independent variables are interactions between the quarterly average water scarcity variables and fuel type. Water scarcity variables contain PDSI (Column 1–4), SPEI (Column 5–8) and Precipitation (Column 9–12). Fuel type dummy variables include coal and hydro technologies. Q1-Q4 represent intervals from January to March, April to June, July to September and October to December, respectively. CDD is a nonlinear climatic variable for cooling degree days. Other control variables contain installed capacity, electricity price and fixed assets investment. Robust standard errors adjusted for clustering at the power plant-year level are in parentheses. The sample spans 2007 through 2014. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

AT3: Nonlinear effects of water scarcity

Dependent variable Ln(generation)	Model_ PDSI				Model _ PDSI × Coal			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PDSI×Bin1(×Coal)	0.087**	0.085**	0.067*	0.068	0.117***	0.107***	0.100***	0.097***
	[0.017,0.156]	[0.010,0.160]	[−0.007,0.140]	[−0.018,0.153]	[0.061,0.173]	[0.044,0.171]	[0.041,0.159]	[0.030,0.165]
PDSI×Bin2(×Coal)	0.056***	0.054***	0.048**	0.047**	0.059***	0.049***	0.055***	0.048***
	[0.018,0.095]	[0.013,0.095]	[0.009,0.088]	[0.001,0.092]	[0.033,0.086]	[0.019,0.080]	[0.027,0.083]	[0.016,0.081]
PDSI×Bin3(×Coal)	0.046***	0.047***	0.039***	0.040***	0.042***	0.036***	0.038***	0.035***
	[0.021,0.071]	[0.021,0.073]	[0.014,0.063]	[0.012,0.067]	[0.022,0.063]	[0.012,0.060]	[0.017,0.059]	[0.010,0.060]
PDSI×Bin4(×Coal)	0.029***	0.033***	0.023***	0.028***	0.026***	0.023**	0.024***	0.025**
	[0.015,0.043]	[0.015,0.050]	[0.008,0.038]	[0.011,0.046]	[0.011,0.041]	[0.005,0.042]	[0.008,0.039]	[0.006,0.044]
PDSI×Bin5(×Coal)	0.015	0.017	0.01	0.012	0.014**	0.012	0.01	0.01
	[−0.008,0.039]	[−0.006,0.040]	[−0.013,0.032]	[−0.011,0.035]	[0.001,0.027]	[−0.003,0.027]	[−0.003,0.023]	[−0.006,0.026]
PDSI×Bin6(×Coal)	0.009	0.01	0.003	0.005	0.009	0.004	0.005	0.002
	[−0.008,0.025]	[−0.010,0.030]	[−0.012,0.019]	[−0.013,0.023]	[−0.016,0.035]	[−0.017,0.025]	[−0.019,0.030]	[−0.020,0.024]
PDSI×Bin7(×Coal)	0.068***	0.056***	0.061***	0.048***	0.064**	0.050***	0.060**	0.046***
	[0.023,0.113]	[0.020,0.092]	[0.017,0.105]	[0.013,0.084]	[0.014,0.115]	[0.014,0.086]	[0.013,0.107]	[0.011,0.080]
CDD	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1800	1800	1800	1800	1800	1800	1800	1800
No. of power (coal) plants	225	225	225	225	195	195	195	195
Within R-squared	0.110	0.105	0.109	0.103	0.109	0.105	0.109	0.102
Plant fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Power grid × Year fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Power plant type × Year fixed effects	No	No	Yes	Yes	No	No	Yes	Yes

Notes: The table presents results for nonlinear effects of water shortage. The dependent variable is the logarithm of generation at the plant level. The key independent variables are interactions between the yearly average PDSI and its distribution bins in Column 1–4 and interactions of fuel type, yearly average PDSI and its distribution bins in Column 5–8. Water scarcity index of PDSI distribution is disaggregated into Bin1 to Bin7, defined as (, –5), [–5, –3), [–3, –1), [–1, 1), [1,3), [3,5) and [5,), respectively. 95% confidence intervals in brackets. CDD is a nonlinear climatic variable for cooling degree days. Other control variables contain installed capacity, electricity price and fixed assets investment. Robust standard errors adjusted for clustering at the power plant-year level. The sample spans 2007 through 2014. * p < 0.10, ** p < 0.05, *** p < 0.01.

AT4: Nonlinear effects of water scarcity

Dependent variable	**Model_ PDSI**				**Model _ PDSI × Coal**			
Ln(generation)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PDSI×Bin1(×Coal)	0.079**	0.076*	0.058*	0.057	0.101***	0.096***	0.079***	0.076**
	[0.008,0.150]	[–0.005,0.156]	[–0.009,0.125]	[–0.022,0.136]	[0.047,0.155]	[0.032,0.159]	[0.023,0.135]	[0.009,0.144]
PDSI×Bin2(×Coal)	0.052***	0.049**	0.044***	0.041**	0.045***	0.039***	0.038***	0.033**
	[0.020,0.083]	[0.012,0.086]	[0.015,0.072]	[0.007,0.074]	[0.021,0.069]	[0.011,0.067]	[0.013,0.064]	[0.002,0.063]
PDSI×Bin3(×Coal)	0.029***	0.031***	0.023**	0.025**	0.024***	0.021**	0.019**	0.019*
	[0.011,0.049]	[0.008,0.053]	[0.006,0.040]	[0.005,0.046]	[0.009,0.040]	[0.002,0.040]	[0.002,0.035]	[–0.002,0.039]
PDSI×Bin4(×Coal)	0.023***	0.024***	0.017**	0.019**	0.018**	0.016**	0.0140*	0.013
	[0.007,0.037]	[0.007,0.041]	[0.002,0.031]	[0.003,0.034]	[0.004,0.032]	[0.000,0.032]	[–0.000,0.029]	[–0.004,0.030]
PDSI×Bin5(×Coal)	0.008	0.009	0.002	0.004	0.004	0.003	–0.001	–0.001
	[–0.005,0.022]	[–0.006,0.025]	[–0.011,0.016]	[–0.010,0.019]	[–0.008,0.016]	[–0.011,0.016]	[–0.013,0.011]	[–0.016,0.013]
PDSI×Bin6(×Coal)	0.066**	0.051**	0.060**	0.044*	0.064*	0.046**	0.060*	0.041*
	[0.008,0.124]	[0.007,0.096]	[0.004,0.116]	[–0.001,0.088]	[–0.000,0.129]	[0.000,0.092]	[–0.001,0.121]	[–0.005,0.087]
CDD	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1800	1800	1800	1800	1800	1800	1800	1800
No. of power (coal) plants	225	225	225	225	195	195	195	195
Within R-squared	0.109	0.104	0.108	0.101	0.109	0.105	0.108	0.101
Plant fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Power grid × Year fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Power plant type × Year fixed effects	No	No	Yes	Yes	No	No	Yes	Yes

Notes: The table presents results for nonlinear effects of water shortage. The dependent variable is the logarithm of generation at the plant level. The key independent variables are interactions between the yearly average PDSI and its distribution bins in Column 1–4 and interactions of fuel type, yearly average PDSI and its distribution bins in Column 5–8. Water scarcity index of PDSI distribution is disaggregated into Bin1 to Bin6, defined as (, –5), [–5, –2) [–2, 0) [0,2), [2,5) and [5,), respectively. 95% confidence intervals in brackets. CDD is a nonlinear climatic variable for cooling degree days. Other control variables contain installed capacity, electricity price and fixed assets investment. Robust standard errors adjusted for clustering at the power plant-year level. The sample spans 2007 through 2014. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

AT5: Placebo tests

Dependent variable Ln(generation)	Model _ NEW				Model _ SF			
	(1)		(2)		(3)		(4)	
PDSI × Coal	–0.123**	(0.061)	–0.103*	(0.0621)	–0.121**	(0.057)	–0.096	(0.060)
PDSI × Hydro	0.692***	(0.150)	0.789***	(0.153)	0.611***	(0.208)	0.721***	(0.231)
PDSI × Nuclear	–0.954***	(0.366)	–0.730*	(0.403)	–1.011***	(0.360)	–0.871**	(0.433)
NEW × Coal	0.005	(0.005)	0.004	(0.006)				
NEW × Hydro	–0.028***	(0.007)	–0.025***	(0.006)				
NEW × Nuclear	0.005	(0.004)	0.005	(0.004)				
SF × Coal					0.003	(0.003)	0.008	(0.006)
SF × Hydro					0.011***	(0.003)	0.011***	(0.003)
SF × Nuclear					0.022*	(0.012)	0.031*	(0.019)
CDD	Yes		Yes		Yes		Yes	
Control Variables	Yes		Yes		Yes		Yes	
Observations	1800		1800		1800		1800	
Number of Coal plants	195		195		195		195	
Number of Hydro plants	25		25		25		25	
Number of Nuclear plants	5		5		5		5	
Within R-squared	0.117		0.114		0.128		0.128	
Plant fixed effects	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
Power grid × Year fixed effects	No		Yes		No		Yes	

Notes: The table presents the comparable results for newly built generators or the regular maintenance and effects of water scarcity. The dependent variable is the logarithm of generation at the plant level. The key independent variables are interactions between the yearly average PDSI and fuel type as well as interactions between actual completed investment on new electric power construction (NEW) and fuel type in Column 1–2. The key independent variables are interactions between the yearly average PDSI and fuel type as well as interactions between service factor (SF) and fuel type in Column 3–4. CDD is a nonlinear climatic variable for cooling degree days. Other control variables contain installed capacity, electricity price and fixed assets investment. Robust standard errors adjusted for clustering at the power plant-year level are in parentheses. The sample spans 2007 through 2014. * p < 0.10, ** p < 0.05, *** p < 0.01.

AT6: Water scarcity effect on the choice of thermal power technology for cooling

Dependent variable Ln(generation)	Model _ CT		Model _ CT		Model _ CT		Model _ CT	
	(1)		(2)		(3)		(4)	
PDSI × Once-through	–0.302***	(0.094)	–0.227**	(0.093)	–0.293***	(0.092)	–0.214**	(0.091)
PDSI × Recirculating	–0.194**	(0.086)	–0.202**	(0.100)	–0.191**	(0.085)	–0.201**	(0.100)
PDSI × Other I for coal	0.050	(0.078)	0.054	(0.076)	0.052	(0.077)	0.058	(0.076)
PDSI × Other III for nuclear	–0.954**	(0.378)	–0.901**	(0.378)	–1.372***	(0.429)	–1.344***	(0.378)
CDD	Yes		Yes		Yes		Yes	
Control variables	Yes		Yes		Yes		Yes	
Observations	1600		1600		1600		1600	
No. of coal plants	195		195		195		195	
No. of nuclear plants	5		5		5		5	
Within R-squared	0.114		0.112		0.110		0.106	
Plant fixed effects	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
Power grid × Year fixed effects	No		Yes		No		Yes	
Power plant type × Year fixed effects	No		No		Yes		Yes	

Notes: The table presents results for effects of water scarcity on the choice of thermal power technology for cooling. The dependent variable is the logarithm of power generation at the plant level. The key independent variables are interactions between yearly average PDSI and electricity generators' cooling technology. Other I for coal refers to power plants for which adapt dry cooled and hybrid cooled systems. CDD is a nonlinear climatic variable for cooling degree days. Other control variables contain installed capacity, electricity price and fixed assets investment. Robust standard errors adjusted for clustering at the power plant-year level are in parentheses. The sample excludes hydroelectricity plants and spans 2007 through 2014. * p < 0.10, ** p < 0.05, *** p < 0.01.

AT7: Water scarcity effect on technology of thermal plants by water sources

Dependent variable Ln(generation)	Model _ WS (1)		Model _ WS (2)		Model _ WS (3)		Model _ WS (4)	
PDSI × Surface water	–0.227**	(0.091)	–0.215**	(0.099)	–0.227**	(0.091)	–0.217**	(0.100)
PDSI × Groundwater	0.322**	(0.145)	0.285*	(0.148)	0.330**	(0.145)	0.290*	(0.148)
PDSI × Municipal wastewater	–0.413	(0.288)	–0.390	(0.288)	–0.409	(0.290)	–0.388	(0.289)
PDSI × Seawater	–0.144	(0.119)	–0.091	(0.099)	–0.130	(0.118)	–0.077	(0.097)
PDSI × Other	–0.006	(0.064)	0.007	(0.068)	–0.004	(0.064)	0.010	(0.068)
CDD	Yes		Yes		Yes		Yes	
Control variables	Yes		Yes		Yes		Yes	
Observations	1600		1600		1600		1600	
No. of coal plants	195		195		195		195	
No. of nuclear plants	5		5		5		5	
Within R-squared	0.161		0.155		0.162		0.155	
Plant fixed effects	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
Power grid × Year fixed effects	No		Yes		No		Yes	
Power plant type × Year fixed effects	No		No		Yes		Yes	

Notes: The table presents results for effects of water scarcity on the technology by water sources. The dependent variable is the logarithm of power generation at the plant level. The key independent variables are interactions between yearly average PDSI and electricity generators' water sources. Other water source refers to electricity plants that do not consume or withdraw water or where their water source is not indicated. CDD is a nonlinear climatic variable for cooling degree days. Other control variables contain installed capacity, electricity price and fixed assets investment. Robust standard errors adjusted for clustering at the power plant-year level are in parentheses. The sample excludes hydroelectricity plants and spans 2007 through 2014. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

AF1: Status quo of electricity generation and CO2 emissions in China

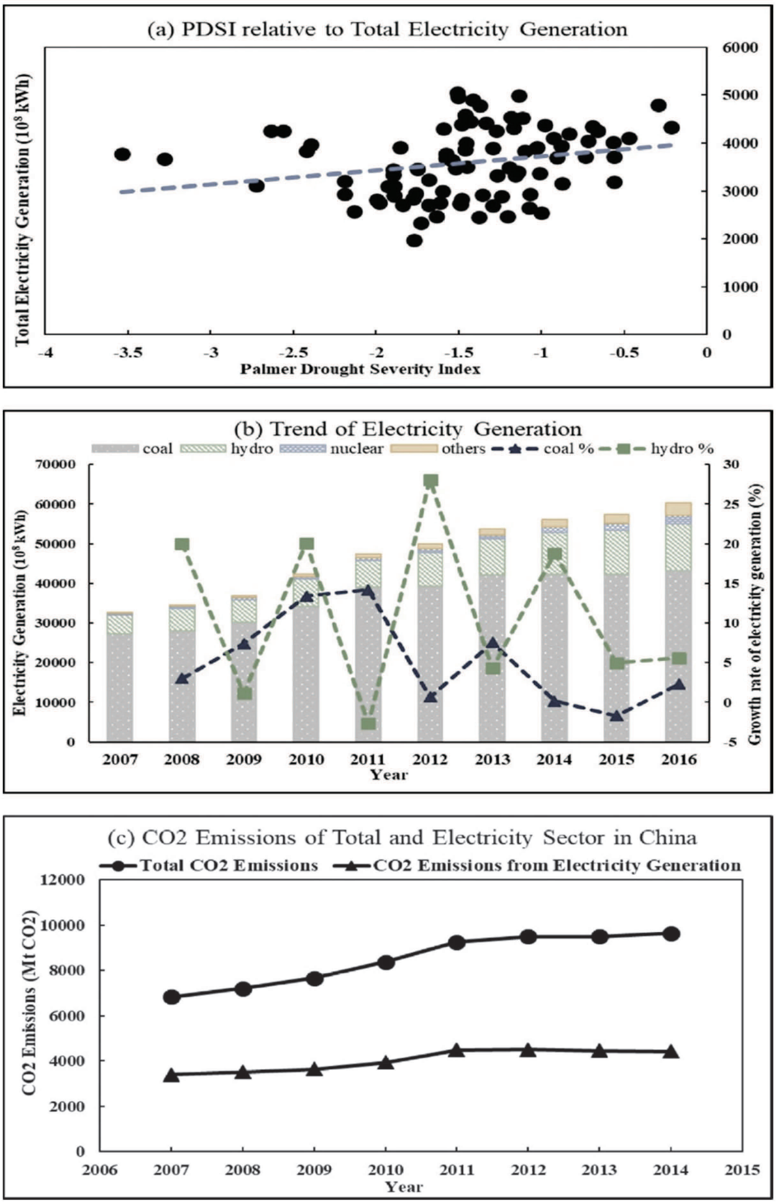

Figure (a) displays correlation between monthly Palmer Drought Severity Index (PDSI) and monthly total electricity generation over the sample period. Figure (b) represents yearly electricity generation and growth by fuel type over time. Figure (c) shows yearly CO_2 emissions of total and electricity sector.
Source: China Energy Statistical Yearbook (2008–2017), China Statistical Yearbook (2008–2017), The Climate Data Guide (2019), China Emission Accounts and Datasets (CEADs) (2007–2014).

AF2: Monthly variation of national precipitation, temperature, Palmer Drought Severity Index and Standardized Precipitation Evapotranspiration Index

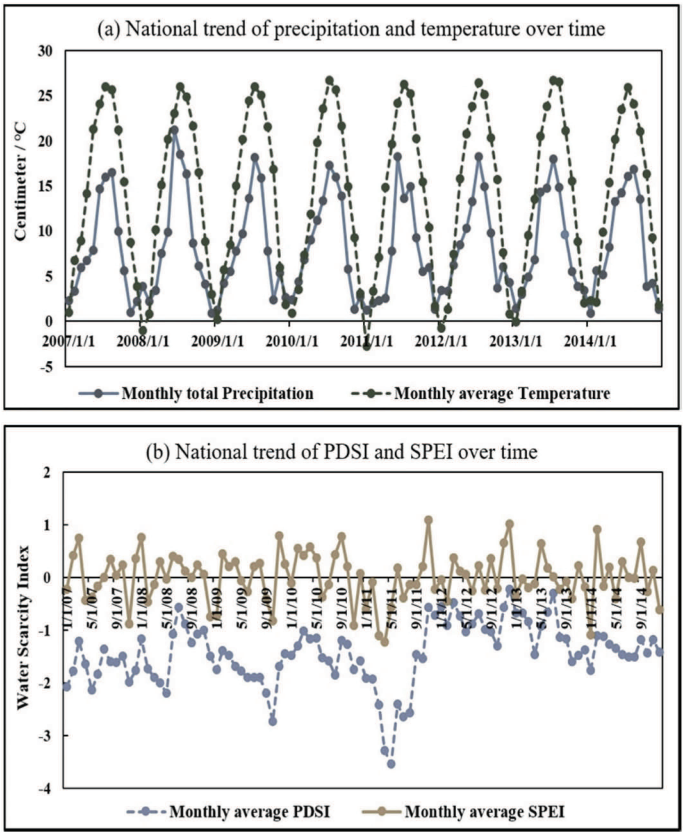

Figure (a) shows monthly total precipitation over time relative to average temperature at the national level. Figure (b) displays monthly average Palmer Drought Severity Index (PDSI) over time relative to monthly average Standardized Precipitation Evapotranspiration Index (SPEI).

Source: The Climate Data Guide (2019), Terrestrial Air Temperature and Precipitation (2017).