Electricity Prices, River Temperatures, and Cooling Water Scarcity

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ABSTRACT. *Thermal-based power stations rely on water for cooling purposes. These water sources may be subject to incidents of scarcity, environmental regulations, and competing economic concerns. This paper analyzes the effect of water scarcity and increased river temperatures on German electricity prices from 2002 to 2009. Having controlled for demand effects, the results indicate that the electricity price is significantly impacted by both a change in river temperatures and the relative abundance of river water. An implication is that future climate change will affect electricity prices not only through changes in demand, but also via increased water temperatures and scarcity.* (JEL Q25, Q41)

I. INTRODUCTION

Thermal-based power facilities, such as nuclear and coal-fired plants, are critically dependent on water for cooling purposes. This enables them to maintain high production efficiencies but also means that they use tremendous volumes of water every day. To give an indication of scale, the thermal industry accounts for roughly 40% of all freshwater withdrawals in the United States—a figure that places it alongside the agricultural sector (USDOE 2006). Unlike agriculture, the majority of these withdrawals are actually returned to their natural source. Discharging used cooling water back into the environment nevertheless presents problems of its own. The excess thermal energy absorbed by cooling water during the heat exchange will naturally cause it to warm up prior to being released back into the river or lake from which it was taken. This raises the ambient temperature of the water source itself and can ultimately cause detrimental effects to the aquatic ecosystem. Water temperatures at or above the mid-20s degrees Celsius (°C) mark are considered particularly dangerous to aqueous plants and certain fish species, since this leads to reduced oxygen levels and raised concentrations of ammonia (Langford 1990). As a result, many countries have enacted environmental regulations on the maximum allowable temperature of discharge water from power stations, otherwise known as "thermal pollution."[1]

Within this context, an emerging literature has developed that seeks to analyze how thermal-based power production might be constrained by access to water resources. Some studies largely abstract from wider climate phenomena and focus primarily on what growing energy demand means for water consumption (e.g., Feeley et al. 2008; USDOE/NETL 2009a, 2009b, 2009c). Others have specifically tried to incorporate climate change into their analysis and even suggest adaptive strategies available to the thermal power industry in coping with a warming world.[2] The *Fourth Assessment Report of the*

[1] The vulnerability to water scarcity, as well as problems related to thermal pollution, varies according to fuel type and cooling technology. For example, the low thermal efficiencies of nuclear plants make them particularly susceptible to water-related issues (e.g., USDOE 2006).

[2] The links between thermal-based power production, water scarcity, and climate have also received growing attention in the popular media. This includes news stories of European power plants shutting down during heat waves of the last decade (Gentleman 2003; Godoy 2006; Pagnamenta 2009) and similar problems in the United States (Associated Press 2008; Sohn 2011; Eaton 2012), as well as implications of the nuclear power sector's dependency on water and recurring incidents of drought (Kanter 2007; Dell'Amore 2010). The linkage between power supply and water needs has also received increased attention in the wake of recent events at the Fukushima Daiichi nuclear plant in Japan (Chellaney 2011).

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Intergovernmental Panel on Climate Change (IPCC 2007) synthesized several such studies in suggesting that future energy generation will be vulnerable to higher temperatures and a reduced availability of cooling water for thermal power stations. Citing effects from the 2003 European heat wave as a precautionary example, the report declared: "Electricity production was undermined by the facts that the temperature of rivers rose, reducing the cooling efficiency of thermal power plants (conventional and nuclear) and that flows of rivers were diminished" (p. 367). Though typically local in focus, the list of individual studies covering equivalent issues includes those by Hurd and Harrod (2001), Arnell et al. (2005), Maulbetsch and DiFilippo (2006), Kirshen, Ruth, and Anderson (2008), Sovacool (2009), and Sovacool and Sovacool (2009).

In terms of predictive capability, Koch and Vögele (2009) offer a more adaptable framework that lends itself to scenario analysis. They do so by constructing an integrated water management model that can be used to simulate the interconnected effects of changing energy needs and water availability on thermal-based power production. This model is then applied to individual plants under various hypothetical climate and economic scenarios. However, while Koch and Vögele go on to comment on some broader socioeconomic outcomes, they acknowledge that their simulations do not account for the fact that "water shortages affecting large regions . . . could have an impact on energy prices" (p. 2039). Förster and Lilliestam (2010) adopt a somewhat narrower approach by simulating the effects of climate change on a single, large (hypothetical) nuclear plant in Central Europe that is reliant on once-through cooling technology. Their results indicate that annual load losses could be as high as 11.8%, with annual plant losses upward of €100 million for the worst-case scenarios. In turn, van Vliet et al. (2012) provide a more general overview of how the power sector will be affected by climate change. Their simulations show that the average summer capacity of power plants in Europe and the United States will be reduced by 6.3% to 19% and 4.4% to 16%, respectively, depending on cooling system type and climate scenario for 2031–2060. They too, however, make no explicit attempts to model for an effect on electricity prices.

In contrast to the simulation-based studies named above, Linnerud, Mideksa, and Eskeland (2011) tread a largely empirical line. Using European data to analyze the impact that climate change may have on the nuclear industry, they find that an average temperature rise of 1°C reduces the supply of nuclear power by roughly half a percent. Finally, Kopytko and Perkins (2011) provide a more discursive overview of the inherent vulnerabilities that nuclear power will be exposed to as a result of climate change. Among other things, they specifically highlight cooling water scarcity as a key impediment to future investment in inland nuclear plants.

The purpose of this paper is to determine how electricity prices are impacted by access to cooling water. Indeed, despite a growing literature on the sensitivity of thermal-based power production to water-related factors, we are unaware of any studies that establish an empirical effect on the price of electricity.[3] Our aim is to quantify what these effects are and, in doing so, provide fresh insight into how the power industry's dependence on cooling water yields direct economic costs.

We use German data in this study and this has several advantages. First, at a total consumption level of around 550 TWh in 2010, the German power market is the largest in Europe and is characterized by a diverse mix of input fuels (Kristiansen 2011). The market is also characterized by a large number of power plants scattered around the country. That said, four companies alone are responsible for approximately 80% of total production capacity (Müsgens 2006; Möst and Genoese 2009). During the 2002–2009 review period of this paper, the country derived approximately 60% of its electricity needs from fossil fuels (mostly coal), 23% from nuclear, and the re-

[3] Boogert and Dupont (2005) suggest that water temperatures resulted in increased Dutch electricity prices (via a supply-side shock) during the 2003 heat wave. However, their concise paper does not offer any empirics beyond some descriptive statistics.

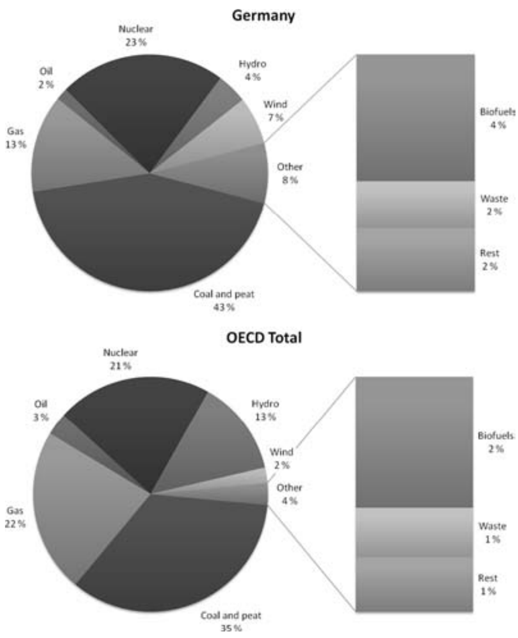

FIGURE 1
Final Electricity Demand in 2009
Source: International Energy Agency

mainder from a combination of renewables.[4] According to the International Energy Agency and as shown in Figure 1, these numbers very closely parallel those of the Organisation for Economic Co-operation and Development region as a whole (IEA 2011a).[5] Germany is therefore a very reasonable "representative agent," from which one can make wider inferences about the impact that water scarcity has on thermal power production and, consequently, electricity prices.

The second factor in support of Germany as a case study is the availability of a wide series of relevant data—including wholesale electricity data and hydrological records—which makes it an amenable choice for conducting empirical analysis. The German power market was fully liberalized in 1998, and by 2001 the major electricity trading platforms had merged to form a single entity, the Leipzig-based European Energy Exchange (EEX). With regard to institutional settings, market participants on the EEX are able to trade a variety of products corresponding to different time horizons and derivative positions. A range of standardized products are also traded in the form of bilateral over-the-counter agreements between direct counterparties, often concluded via brokerage firms.

This paper uses data on the day-ahead EEX spot auction, during which hourly electricity contracts and block contracts can be traded until midnight of the previous day.[6] The EEX spot market accounts for approximately 30% of German electricity demand, and we would certainly expect marginal changes in river levels or temperatures to be reflected in these prices. Furthermore, the spot price also acts as a reference point for *all* upstream market participants, regardless of where and what they are trading. If not, there would be costless arbitrage opportunities (Viehmann 2011; Kristiansen 2011). The day-ahead spot market should thus not only reflect the underlying long-term demand and supply conditions of the power sector, but also respond to short-term shocks. This includes power plants being entered into constrained production due restrictions on their intake of cooling water.

The third and perhaps most important reason for using the German data, is that the country's electricity sector has proven vulnerable to incidences of water scarcity and com-

[4] The role of nuclear power in Germany has been highly contested over the last several decades, with renewed public interest in the wake of the stricken Fukushima Daiichi plant in Japan. Following a period of political flip-flopping on the issue, the German government in 2011 committed to phasing out nuclear power by 2022. However, we do not explicitly consider these developments in this paper, since they took place after the relevant period of study.

[5] The relative role that thermal-based power plays is comparable even at a global level, where the contributions of fossil fuels and nuclear to total power generation in 2009 were 67% and 13%, respectively (IEA 2011b).

[6] Instead of using average daily prices, one might be tempted to argue that higher-frequency data (e.g., hourly) would allow for a higher degree of analytical precision. There are several reasons why we do not follow this approach. First, the supply of produced electricity is not particularly flexible for the baseload plants that we focus on in this study. Second, environmental authorities are highly unlikely to respond to changes on an hourly basis, but rather issue daily orders to power plant operators. Third, daily data is consistent with our other data (e.g., hydrological).

promised water quality in the past. This has been especially true during very hot periods such as the European heat waves in 2003 and 2006, when Germany joined the likes of France and Spain in suffering from significantly reduced production capacities. A proximate cause of this outcome was the fact that river temperatures began to exceed the regulatory threshold imposed on thermal water pollution. Faced with a power system already straining under the pressure of unusually high demand for cooling, German federal authorities initially provided emergency dispensation for power stations to flout environmental laws. However, they were eventually forced to uphold the standard restrictions on discharging hot water into the environment in order to protect river fauna and flora. Overall, at least 15 thermal plants had to be shut down or entered into constrained production because of water-related issues during the summer months of 2003 (Müller, Greis, and Rothstein 2007, 2008). Similarly, at least 12 plants were throttled during the 2006 heat wave so as to limit the discharge of thermal wastewater into rivers (Müller, Grels, and Rothstein 2007, 2008).

It is against this backdrop that we can preview the key findings of this paper. Having successfully controlled for various demand-side effects, our empirical results indicate that the electricity price is significantly impacted by both a change in river temperatures and the relative abundance of river water. Falling river levels are generally associated with a higher electricity price, while prices will also be driven higher once average river temperatures breach regulatory thresholds. For instance, we estimate that an increase in average river temperatures from 25°C to 26°C will bring about a near 4% increase in electricity prices over the course of a week.

II. THEORETICAL MODEL AND ECONOMETRIC STRATEGY

Our model aims to incorporate the thermal production process—albeit in a highly stylized manner—to account for the effect that increased river temperatures have on electricity output. In brief, thermal energy can be converted into electrical energy more efficiently in the presence of an external coolant, such as water.[7] This allows excess heat from the production cycle to be transferred to the coolant and subsequently disposed of. The cooling technology that thermal-based power plants use may be divided into two broad categories: once-through systems and closed-circuit systems. The former requires that far greater volumes of water be withdrawn from natural sources, while the latter "consumes" more in the form of evaporation. That said, we abstract from such differences and instead focus on the core principle that cooling is essential to maintaining efficiency levels in any thermal-based power plant, irrespective of whether it is fueled by coal, gas, or nuclear energy. We therefore assume a simple production technology of

$$Q = A(T_{\mathrm{EW}} - T) \cdot W. \qquad [1]$$

In other words, the production of electricity Q is contingent on the difference in temperature of the discharge water at the outlet point, T_{EW} , and the cooling water at the intake point, T. Production will increase as this temperature difference increases, since it is assumed that $A' > 0$.[8] This formulation effectively takes the inner workings of the thermal engine as exogenous and instead focuses on the fact that surplus heat energy is transferred to the cooling water via a heat exchange. A higher temperature difference between the discharge water and its original source therefore implies a higher thermal efficiency (i.e., conversion of thermal energy into electrical energy). Importantly, the model also captures the possibility that thermal-based plants can use more cooling water, W, to compensate for a low temperature differential. Figure 2 provides a styl-

[7] This result is famously rendered by Carnot's theorem, which holds that the efficiency of a thermal-based engine is directly proportional to the temperature differential between its high- and low-temperature reservoirs (e.g., Langford 1990).

[8] An underlying assumption is that $T_{\mathrm{EW}} \geq T$. In other words, there is a cooling effect due to the heat exchange that takes place in the plant condenser. The specification that we have used here is thus also indicative of the fact that the cooling effect becomes increasingly negligible as the temperature difference falls.

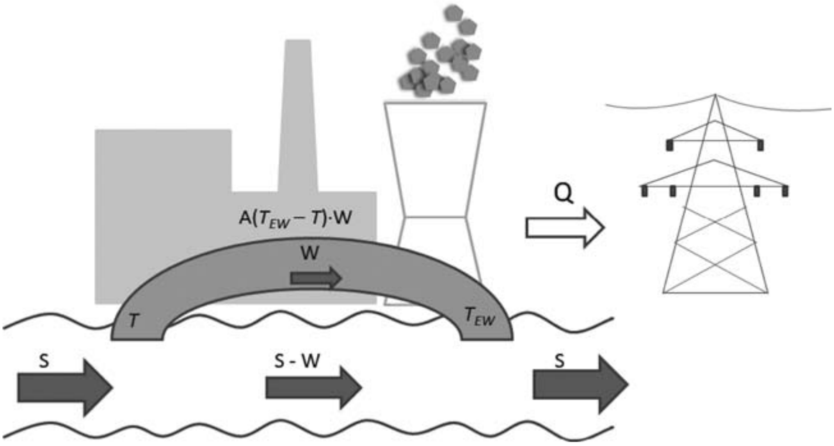

FIGURE 2
Water Intake and Cooling for a Power Plant

ized depiction of the production cycle used in our model.

The production of electricity by thermal-based power stations is subject to the following constraint:

$$\frac{W}{S} \cdot T_{\mathrm{EW}} + \left(\frac{S-W}{S}\right) \cdot T \leq \overline{T}. \qquad [2]$$

This reflects the fact that environmental authorities set a cap, $\overline{T}$, on the temperature of the downstream river volume, S, which occurs as a result of the mixing between discharged cooling water, W, and the river water not used for cooling ($S - W$). Thus, W/S is the share of total river water used for cooling. The constraint implies that rather than undergoing a complete shutdown, the plant has the option of reducing the flow of discharge relative to the volume of downstream mixing water when the temperature of each unit of discharged water, T_{EW}, is relatively hot. However, as the temperature of the river water itself approaches the regulatory limit (e.g., during very hot summer months), the plant has little room for maneuvering and will likely have to decrease output.[9]

The strategic decision variable available to power plants in our theoretical framework is quantity. It should be noted that electricity is a homogeneous product that cannot be stored, and demand must be perfectly balanced by supply at all times. Given the institutional settings of the German power market, our model allows for potential market power but is also generalizable to a situation where the representative power plant behaves as a price-taker. We therefore model the profit, π, for thermal-based plants as follows:

$$\pi = p(Q+F) \cdot Q - c(Q) - p_{\mathrm{w}}(RL) \cdot W, \qquad [3]$$

where $p(\cdot)$ denotes the inverse demand function and total electricity demand is the sum of power produced by the analyzed plants, Q, together with electricity imports and the other sources that are not dependent on cooling water (e.g., wind power), F. The cost function, $c(Q)$, captures the marginal costs associated with the production of additional quantities of electricity. In addition to these standard production costs, the latter part of the expression, $p_{\mathrm{w}}(RL) \cdot W$, reflects the fact that there are

[9] Of course, environmental authorities will also typically impose limits on the temperature of the discharged water itself—let us say $\overline{T}_{\mathrm{EW}}$—and/or on the temperature differential between river water at the intake point and the discharge (cf. Mimler et al. 2009). In the interests of parsimony, however, we ignore these additional limits in our model. Indeed, one could argue that including a constraint, $\overline{T}$, on the temperature of the downstream river volume, S, already serves to capture these effects indirectly.

costs associated with drawing cooling water, W, from its source (here, the river). These are said to be a function of the river level, RL, such that $p_W{}' < 0$.

By substituting in the technology function for the water parameter, W, we have the following profit maximization problem:

$$\max_{Q} p(Q+F)\cdot Q - c(Q) - p_W(RL)\cdot\frac{Q}{A(T_{EW}-T)}, \quad [4]$$

subject to

$$\frac{Q}{S\cdot A(T_{EW}-T)}\cdot T_{EW} + \left(1-\frac{Q}{S\cdot A(T_{EW}-T)}\right)\cdot T \le \overline{T}.$$

Taking the first-order condition with respect to Q yields

$$p^*\left(1-\frac{1}{\varepsilon}\right) = \frac{\partial c(Q^*)}{\partial Q} + p_W(RL)\cdot\frac{1}{A(T_{EW}-T)} + \lambda\cdot\frac{1}{S\cdot A(T_{EW}-T)}\cdot(T_{EW}-T), \quad [5]$$

where Q^* is the optimal level of produced energy (with corresponding optimal price, p^*), λ is the shadow price of the constraint, and ε denotes the price elasticity where we have integrated out the demand effects for electricity provided by the other sources.[10]

Given that $p_W{}' < 0$, a lower river level will effectively have the same impact as an increase in production costs. Falling river levels will consequently reduce the supply of electricity and ultimately bring about an increase in price, that is, $\partial p^*/\partial RL < 0$. The effect of river temperatures is slightly more complex, as it will impact price through various channels. First, an increase in T will negatively impact the thermal efficiency of a plant. This effect could be mitigated by withdrawing more cooling water, although this will bring with it its own costs, since profit is a function of $p_W(RL)\cdot W$. Moreover, when the constraint is binding ($\lambda > 0$), the only way that a power plant can respond to increased river temperatures will be to reduce W and therefore lower the production. In either case, an increase in T will reduce the quantity of electricity by shifting the supply curve to the left. This in turn will lead to an increase in price, that is, $\partial p^*/\partial T > 0$.[11]

[10] This means that the model encompasses settings where the representative plant is a price-taker (i.e., $\varepsilon \to -\infty$), or where it exercises market power. Of course, a plant's ability to react to changes in demand or marginal costs will also depend on what its fuel type is. For instance, nuclear power plants are built for providing a constant baseload, while gas-fired plants are more flexible.

It is well known that electricity prices and quantities are jointly determined in the market-clearing process. This simultaneity needs to be accounted for in the empirical estimation of our theoretical model. We therefore begin by defining the following supply equation:

$$\ln P_t = \beta_0 + \beta_1 \ln Q_t + \beta_2 \ln RL + \beta_3 \ln RT_t + \beta_4 \ln F_t + \beta_T{}'\mathbf{T}_t + v_t, \quad [6]$$

where P is the daily clearing price for electricity, Q is the daily electricity consumption, RL is the aggregated river level, RT is the river temperature, F is fuel (input) costs, and $\mathbf{T}$ is a set of seasonal and trend variables.

The regressors of greatest interest to this study are river levels (RL) and river temperatures (RT). These two coefficients should reflect how electricity supply is constrained by diminished cooling water availability, due to either relative scarcity (i.e., falling river levels) or regulatory concerns (i.e., river temperatures breaching environmentally sensitive thresholds).

The aforementioned simultaneity means that simply regressing electricity prices on quantities using ordinary least squares (OLS) will generate inconsistent parameter estimates. We resolve this issue by adopting an instrumental variable (IV) approach within a two-stage least squares (2SLS) framework. Instrumenting for Q should allow us to properly identify the causal effect that changing volumes have on electricity prices. Our set of instruments begins with a concept widely used in energy modeling, namely, degree days

[11] Please see the Appendix for a more detailed derivation of the comparative statics.

(see, e.g., Halvorsen 1975; Quayle and Diaz 1980). Heating degree days (HDD) and cooling degree days (CDD) are complementary terms that capture the nonlinear effect that changing temperatures have on electricity demand. They do this by measuring the extent to which air temperatures fall outside a given "comfort zone," which we define here as 18°C to 22°C.[12] The *HDD* variable measures how far the temperature drops below 18°C on any given "cold" day (thus requiring heating), while *CDD* measures how far the temperature exceeds 22°C on any given "hot" day (thus requiring cooling).[13] Our set of instruments is completed by a dummy variable that corresponds to nonworking days, *NWD*. This variable is included to reflect the fact that electricity demand typically falls on weekends and public holidays due to reduced industrial activity.

The critical assumption for our chosen instrumental variables—*CDD*, *HDD*, and *NWD*—is that they pass the exclusion restrictions requirement. That is, they affect prices only indirectly through changes in demand. The temperature discomfort associated with *CDD* and *HDD* is thus assumed to cause an increase in demand but have no bearing on direct supply. Given that we control for changing river levels and river temperatures separately, this seems to be a valid assumption. Similarly, it is extremely unlikely that the supply of electricity will be materially constrained by the fact that it is a weekday or public holiday. The main factors of production are not affected by the day of the week, for instance, and power companies will be able operate at normal capacity irrespective of such considerations. To be sure of the exogeneity of the instruments, however, we conduct a Sargan-Hansen overidentification test to confirm our economic reasoning. Furthermore, the standard Durbin-Wu-Hausman specification test is used to test for endogeneity. The Kleibergen-Paap test, a robust variant of the Stock and Yogo (2005) test that allows for non–independent and identically distributed errors, is used to check the validity of our instruments (see Baum, Schaffer, and Stillman 2007). This is complimented by a simple *F*-test of the instruments in the first-stage regression (Staiger and Stock 1997).

III. DATA DESCRIPTION

The data for this paper are collected from several different sources. The data for each series consist of daily values over the period 2002–2009. Data on German spot electricity prices and volumes are obtained from the aforementioned European Energy Exchange AG (EEX). Daily electricity data are available for both base (24-hour continuous) and peak (12 hours from 8 a.m. to 8 p.m.) periods. However, we focus exclusively on the base series in this paper. The primary reason for this is the fact that the power plants most vulnerable to water-related factors, such as nuclear and coal-fired plants, are all baseload electricity operators. Consequently, one would expect that the impact of any supply constraints to these plants will already be visible within the base price. Moreover, having a data point that runs over an entire day helps to ensure consistency with the other variables, which also cover daily time steps. It should also be noted that electricity prices in Germany are geographically uniform with no zonal differentiation.[14] Both electricity prices and volumes are log-transformed for the regression analysis.

Air temperature data are obtained from Deutscher Wetterdienst (German Meteorological Service). To compute aggregate temperature data, daily values are first collected for each capital city of the 16 German federal

[12] This is a fairly standard range in the literature. Some studies (cf. Bessec and Fouquau 2008) contend that the turning point for temperate European countries occurs at slightly lower intervals, from roughly 16°C. Having tested this formally, however, there is no significant difference in using 16°C or 18°C as the threshold for *HDD*s for our data set.

[13] To illustrate, an aggregate daily temperature of 17°C would correspond to one *HDD*, while a temperature of 15°C would equate to three *HDD*s. Similarly, a temperature of 27°C would correspond to five *CDD*s, and so forth.

[14] The regulatory framework of the EEX does allow for the market to be broken up into different price zones when grid capacities are unable to fully execute the spot auction schedules, but this was not necessary during the review period of this study (Ockenfels, Grimm, and Zoettl 2008).

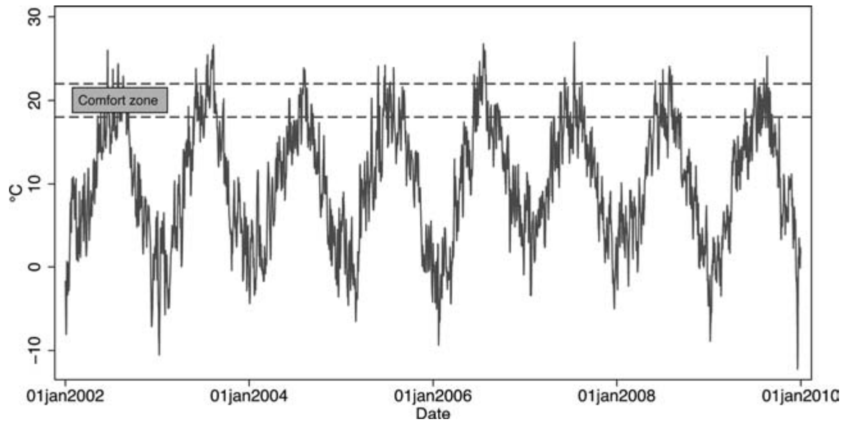

FIGURE 3
Mean Air Temperature

states. In the minority of cases where data limitations mean that a state cannot be represented by its capital, a significant counterpart city is used instead.[15] The mean temperature recording in all of these cities (computed from 24 hourly observations) is then computed into a single daily mean temperature series for the entire country. This aggregating step is taken to ensure consistency with the uniform electricity prices across the German states. Next, we create a set of degree day interaction dummies, *HDD* and *CDD*. These variables are adjusted so as to reflect logged values, that is, $D^{\text{temp}>22^{\circ}} \cdot \log(temp - 22^{\circ})$, and $D^{\text{temp}<18^{\circ}} \cdot \log(18^{\circ} - temp)$. The daily mean air temperature series is shown in Figure 3 together with the designated comfort zone.

Hydrological data, in the form of river levels and temperatures, are provided by the Bundesanstalt für Gewässerkunde (Federal Institute of Hydrology). Data measurements were taken from gauging stations situated at various points along four major German rivers: the Elbe, Main, Neckar, and Rhine. It is worth noting that these rivers acted as the water source for a number of nuclear plants during the 2003–2009 review period, in addition to several coal-fired plants that also suffered reduced capacity due to restrictions on thermal pollution.[16] Our dataset should therefore be able to capture the relevant effects of cooling water scarcity and environmental regulation. To help ensure consistency with our other data, we take the daily averages for each individual river and then use these to construct two series of mean values for the whole country: *RL* (cm) and *RT* (°C).

Apart from being log-transformed, data from the *RL* series are entered directly into the regression model. However, we make two adjustments to the *RT* series to better capture how regulation of thermal pollution impacts electricity prices. The first is to generate a standard dummy variable that tests for a difference in price intercept when river temperatures exceed a defined regulatory limit of 25°C. The second is to specifically measure the continued rise in temperature above this 25°C threshold, that is, $D^{\text{RT}>25^{\circ}} \cdot log(RT - 25^{\circ})$. This formulation is aimed at ensuring some flexibility and allows for a nonlinear temperature effect around the regulatory threshold. It should be noted that our specification here is consistent with the theoretical model described in Section II; a

[15] For instance, data for Wiesbaden, the capital of Hesse, were not available, so these were substituted with data from the much bigger Frankfurt.

[16] The list of nuclear plants includes the Biblis and Philipsburg (Rhine), Brunsbüttel and Krümmel (Elbe), Grafenrheinfeld (Main), and Neckarwestheim and Obrigheim (Neckar). The Obrigheim plant was decommissioned in 2005 but was among those temporarily switched off during the 2003 heat wave due to thermal pollution.

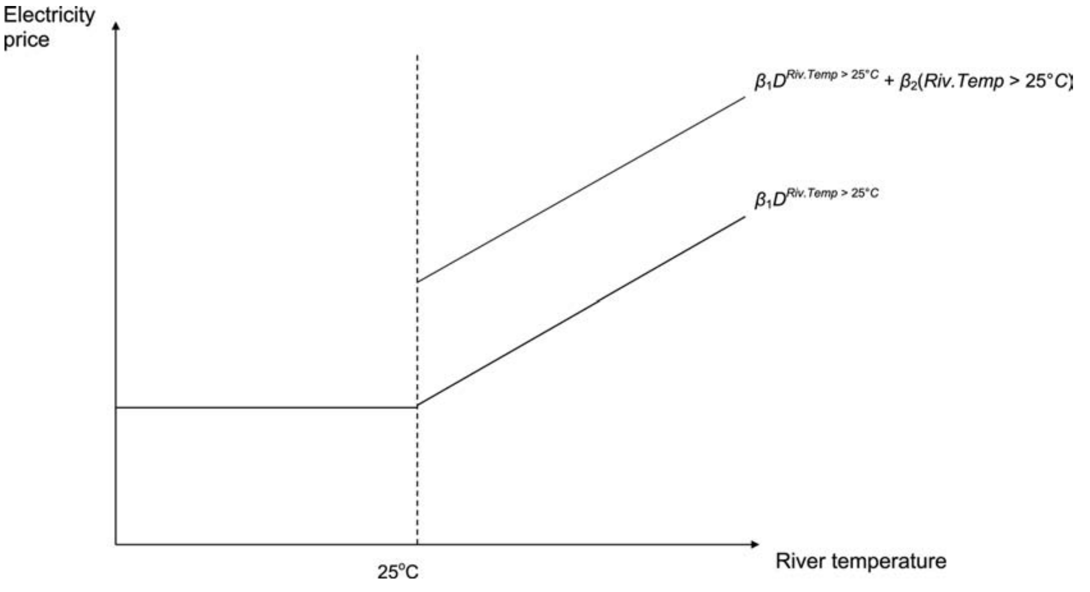

FIGURE 4
The Effect of River Temperatures on Electricity Price

shadow price comes into play when the river temperature is greater than some regulatory limit, with a positive marginal effect on electricity prices as temperatures increase above that threshold. Figure 4 depicts this relationship in a stylized manner.

We use the log-transformed, 90-day moving average (MA) of Brent crude oil to account for the effect that changing fuel (i.e., input) costs have on power production. These are obtained from Bloomberg and adjusted for changes to the USD-EUR exchange rate. While oil-fired plants do not play a substantial role in the German electricity market, oil is widely used as a proxy for natural gas and it is even used within the power industry to forecast the general price movements of coal. The fact that daily spot prices are available for oil also makes it more amenable to our empirical analysis.

Finally, we include a number of parameters in the model to control for trend and seasonality. Month and year dummies are created to pick up the standard seasonal characteristics found in electricity data, as well as unaccounted trends in demand (e.g., those stemming from changes in consumers' aggregate income level over the review period). Furthermore, since electricity consumption is expected to be highly correlated with economic activity, a dummy variable for nonworking days (i.e., weekends and public holidays) is also included in the regression analysis.

IV. EMPIRICAL RESULTS

Our primary estimation results are presented in Table 1. Model 1 is characterized by a static setting that utilizes only contemporaneous variables. Models 2 and 3 are dynamic in the sense that they include lagged electricity price and volume observations as additional regressors. All results have been calculated using heteroskedasticity- and autocorrelation-consistent (HAC) estimators (Newey and West 1987).

Considering Model 1 first, the rationale underpinning this "static" specification is that, given its role as an optimizing market, the spot power exchange should effectively constitute a new market each day. The coefficient on volume (5.976) suggests that a 1% increase in the volume of consumed electricity will induce a 6% increase in the base electricity price. This implies that the daily power supply in Germany is highly inelastic, which we

TABLE 1
Primary Models, Dependent Variable = Price (€/MWh)

	Model 1	Model 2	Model 3
Coefficients			
Volume (1,000 MWh)	5.976*** (0.503)	8.267*** (1.020)	8.233*** (0.998)
Predetermined variables			
L1.Price		0.624*** (0.054)	0.625*** (0.054)
L7.Price		0.138** (0.053)	0.141*** (0.053)
L1.Volume		− 3.729*** (0.466)	− 3.697*** (0.451)
L7.Volume		− 2.280*** (0.372)	− 2.272*** (0.361)
River levels (cm)			
Single series	− 1.025*** (0.234)	− 0.389*** (0.135)	
Splines (by percentiles)			
"Low" (0%–33%)			− 0.206 (0.232)
"Medium" (33%–67%)			− 0.148 (0.303)
"High" (67%–100%)			− 0.580*** (0.223)
River temperature (°C)			
D^{Riv25} ($1 = RT > 25$°C)	0.094 (0.156)	− 0.053 (0.075)	− 0.027 (0.075)
$RT - 25$°C, if > 25°C	0.277*** (0.055)	0.210*** (0.029)	0.218*** (0.029)
Brent (90-day MA, €/bbl)	0.528 (0.442)	0.163 (0.200)	0.149 (0.185)
Tests			
Endogeneity test[a]	1,161.46***	468.01***	473.20***
1SLS instrument joint significance *F*-test	123.65***	36.56***	37.13***
Instrument relevance test[b]	65.01***	23.64***	25.70***
Overidentifying restrictions test[c]	3.21	5.43	5.40
Autocorrelation test[d]	1,604.23***	2.69	2.69
Joint significance tests (χ^2)			
Month dummies	64.76***	35.33***	35.91***
Year dummies	147.73***	42.45***	43.92***
N	2,922	2,915	2,915

Note: All variables are entered in logarithmic form. Standard errors for the coefficients are reported in parentheses. A constant term and year and month dummies are also included as regressors in the price equation. However, the estimated coefficients attached to these variables are not reported in the table. Heating degree days (*HDD*), cooling degree days (*CDD*), and a nonworking day (*NWD*) dummy are used as instruments in the first-stage regression. 1SLS, one-stage least squares; 2SLS, two-stage least squares; HAC, heteroskedasticity- and autocorrelation-consistent; MA, moving average.

[a] Durbin-Wu-Hausman *F*-test includes the saved residuals from the first-stage regression in the second stage of the 2SLS estimation. H_0: System is exogenous.

[b] Kleibergen-Paap Wald *rk F*-statistic. H_0: System is underidentified and the instruments are not relevant (i.e., weak).

[c] The Hansen *J*-statistic for overidentifying restrictions is computed using HAC estimators. H_0: Instruments are exogenous.

[d] The autocorrelation test statistics are the *F*-statistics of the coefficient from a regression where the residual from the main regression is regressed on its own lagged value.

** $p < 0.05$; *** $p < 0.01$.

would expect given the very short term nature of the data used in this study (i.e., daily observations).

Water scarcity, as measured by changes to the average river level, returns a negative coefficient in the static model (− 1.025), indicating that the electricity price is expected to fall by around 1% for every 1% rise in river levels. This is consistent with our earlier hypothesis that electricity prices move in the direction opposite to the availability of cooling water, even after controlling for potential demand effects.

Model 1 also shows that there is a positive, statistically significant relationship between the electricity price and an aggregate river temperature over 25°C. Once this threshold is breached, the price rises by 0.277% with every additional percentage point increase in river temperatures. To put this in perspective, a rise in average river temperatures from 25°C to 26°C would yield an approximate 1.2% increase in the price of electricity. The fact that the $D^{\text{RT}>25°\text{C}}$ dummy returns a statistically insignificant coefficient implies that there is no discontinuity around this 25°C threshold.

Again, this is consistent with our theoretical model in which, rather than simply shutting down, power plants have the option of reducing power to stay within the regulatory limits set by authorities.

While fuel costs are not of special interest to this paper, the coefficient on the 90-day MA for Brent crude is positive but statistically insignificant. (We would expect a positive sign given that fossil fuels serve as an important factor of production in generating electricity.) The set of month and year dummies are not reported on an individual basis, but they are all jointly significant.[17]

Our use of an IV/2SLS approach has been motivated by the fact that prices and quantities are determined simultaneously. This is confirmed by the Durbin-Wu-Hausman test, which shows that endogeneity is a problem and that OLS should be discarded in favor of 2SLS. The Kleibergen-Paap test indicates that our instruments are highly relevant (i.e., no weak instrument problem). We complement this with the recommendation of Staiger and Stock (1997) by using an *F*-test to test the relevance of the instruments in the first stage of the 2SLS. This *F*-statistic is significantly greater than their "rule of thumb" value of 10, and so we again reject the null of weak instruments. In addition, the Hansen's *J*-test of overidentifying restrictions shows that they are also valid.[18]

Applying an augmented Dickey-Fuller test (ADF) on the residuals for Model 1 shows that persistency in the data does not appear to be a problem.[19] However, further testing does reveal the presence of positive autocorrelation. A probable explanation for this is misspecified dynamics—in particular, our reliance thus far on a completely static model specification. Yet it could be argued that today's electricity price is correlated with the previous day's price, or even that of the week before. This idea is given credence by the fact that electricity supply comprises quasi-fixed proportions of baseload and variable power. Baseload facilities such as nuclear and coal-fired power plants are typically constrained in their ability to change output levels.[20] One might therefore argue that there is some "memory" in the power market system and that our modeling efforts could be improved by incorporating dynamic aspects.

The key results from two such dynamic models, which include one- and seven-day lags for both electricity price and volumes, are presented in the second and third columns of Table 1. These lags are chosen to account for the inertia from the previous day and weekday effects. Model 2 is a straightforward extension of our static model, while in Model 3 we want to open up for the possibility that changes in water availability matter at different stages of relative abundance. Thus, the continuous river level series has been replaced by spline partitions. Since the majority of the coefficients of these two models are qualitatively indistinguishable, we consider them together.

It can immediately be seen that the coefficients on the lagged endogenous variables in

[17] There is an increasingly negative coefficient on the year dummy coefficients until 2009, demonstrating that electricity prices have been increasing slowly relative to volumes over the years. Furthermore, the coefficients on the month dummies indicate that German electricity prices are typically higher in the summer months.

[18] It could be argued that our *CDD* instrument has a potentially direct effect on electricity supply, since high air temperatures—the basis for *CDD*—and river temperatures are correlated, albeit with a lag of several days. The increase in river temperatures implies a higher likelihood of regulatory enforcement. If so, there could be a direct link between *CDD* and supply of electricity that consequently violates the exogeneity assumption. In the spirit of an overidentification test, we have therefore run an auxiliary 2SLS that only uses our other two instruments: *HDD* and *NWD*. These two instruments are exogenous by assumption, and we have no cause to think that they should be correlated with high river temperatures. We find that the predicted residuals of this auxiliary regression are not correlated with the debatable instrument *CDD* (p-value = 0.180). This suggests that *CDD* is a valid instrument in our setting.

[19] Although not reported, it is also tested whether persistency (i.e., nonstationarity) is a problem for the log-transformed electricity prices and volumes using an ADF test. Having accounted for trends in the form of year and monthly dummies we are able to reject the null hypothesis of nonstationarity for these series.

[20] The load-following capacity of baseload power is an important concept here. In particular, nuclear and coal-fired plants are normally run continuously at a more or less constant level of output. This is both a matter of economic efficiency (since they have low variable costs in comparison with the high fixed costs that must be recouped) and technical efficiency (since these plants cannot readily alter power output in the same way that gas or hydro plants can). See, for instance, WNA (2011).

both dynamic models are all statistically significant. This goes some way toward vindicating our suspicions that the German electricity spot exchange does not simply constitute a "new" market every day. Illustrating by way of Model 2, the coefficient on the contemporaneous volume of electricity (i.e., 8.267) denotes the short-run, instantaneous impact of a change in quantity on price. The corresponding long-run multiplier is found by incorporating the lagged endogenous variables of our model and can be calculated as $[(8.267 - 3.729 - 2.28)/(1 - 0.624 - 0.138)] = 9.487$. Testing this figure reveals it to be statistically significant at the 1% level. The dynamic model specification therefore predicts that a 1% increase in electricity volumes will lead to a 9.5% increase in price over the course of a full week. Again, this describes a very inelastic supply curve, but it is representative of the inertia present within the power system.

Looking next at the effect of river temperatures, both dynamic models show that there is a positive impact on electricity prices once the 25°C threshold is breached. A 1% increase in river temperatures above this mark will yield an increase in contemporaneous prices slightly greater than 0.2%. The equivalent long-run effect is closer to 0.9%. Thus, a temperature rise from 25°C to 26°C would bring about an immediate price increase of approximately 0.9%, or equivalently, an increase of 3.8% over the next seven days. Once more, these effects are all statistically significant at the 1% level.

The key distinction between our two dynamic models lies in the way that they measure the impact of changing river levels. Model 2 is a straightforward extension of Model 1 in that it uses a single, continuous series. Like its static counterpart, Model 2 suggests a negative relationship with the electricity price: A 1% drop in river levels is associated with a 0.4% rise in the concurrent electricity price, while the relevant long-run multiplier suggests an approximate 1.6% rise over the course of a week.

For Model 3, we split the river level series into three splines of equal size based on percentile distribution: (1) "low" (0%–33%); (2) "medium" (33%–67%); and (3) "high" (67%–100%).[21] Only changes within the "high" river level category are shown to be statistically significant: A 1% drop in river levels within this range will lead to a 0.6% rise in contemporaneous prices, or a 1.8% rise in the long run. A potential explanation for the insignificance of the "medium" and "low" river level splines could be that those plants most reliant on water consumption—in other words, those most sensitive to water scarcity—have already been forced to power down by the time that rivers reach their lowest levels. Regardless, formal testing reveals that the coefficient on the "mid" spline is statistically indistinguishable from that of the "high" spline (p-value = 0.31). Conducting a similar test on the "low" spline coefficient reveals that it too is statistically identical to the "high" spline (p-value = 0.18). As a consequence of these tests, it makes sense to do away with the separate splines and simply include river levels as a single continuous series as in our preferred specification, Model 2.

Running through the same set of statistical tests described previously, we are able to confirm the validity of our instruments (as well as the presence of endogeneity that necessitates the use of an IV approach in the first place). A more pertinent question concerning the extension toward a dynamic specification, however, is whether it removes the autocorrelation that was present in the static models. It is well known that in addition to efficiency concerns, inclusion of the lagged dependent variable will lead to biased coefficient estimates in the presence of serially correlated residuals. That said, testing reveals that autocorrelation is not present in any of the dynamic models. This adds further credibility to the notion that the dynamic specification of our model is preferable to its static counterpart.[22]

In addition to the primary models presented in Table 1, we have run a number of

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[21] Admittedly, these splines are chosen somewhat arbitrarily. However, having experimented with different cut-off points, our conclusion is that the main results are robust to such changes.

[22] While of lesser importance to this study, we also note that the coefficient on fuel costs remains insignificant under the dynamic specification.

alternate specifications and supplementary regressions to confirm the robustness of our findings.[23] First, instead of using month dummies, we have also tried to control for seasonal effects by incorporating a trigonometric wave function in the models.[24] Doing so does not change our results in any material way. Second, we have replaced the splines of Model 3 with a set of dummies that similarly divides the river level series into equal thirds ("low," "middle," and "high") based on the overall distribution. Rather than measuring the potential difference in slope coefficients, the aim here is to assess whether there are any statistically significant differences in the intercepts of the different river level groups. Again, we find that electricity prices will be driven higher as river levels fall.[25]

By focusing on high river temperatures (i.e., 25°C and above), our goal has been to capture the impact that regulatory constraints have on power supply. Such regulatory interventions are a direct result of the increased river temperatures that are measured directly in our analysis. In addition, by holding our data together with shutdown dates collected by Müller, Greis, and Rothstein (2007), we find a jump in prices during the period of regulatory enforcement compared with those immediately preceding and/or following them.[26] There is also an uncanny overlap between these days and times where the average river temperature exceeds the 25°C mark. We view this as supplementary evidence in favor of our analysis of the effects of regulatory actions and increased river temperature, as well as our defined regulatory threshold.[27]

So far, we have followed an aggregated approach with regard to both river level and river temperature. This decision has primarily been motivated by the fact that Germany has a single electricity price common to all regions. Moreover, the purpose of this paper is to essentially test for *systematic* risks, particularly with regard to river temperatures and the regulation of thermal pollution. However, it could still be asked whether the individual rivers in our dataset are similar enough to warrant this type of aggregation. We have therefore subjected our data to several robustness checks. First, we construct a simple correlation matrix of the (detrended) individual river temperature series.[28] These correlation coefficients fall within the interval [0.80, 0.94] and are highly significant. We have also looked at the share of individual temperature observations that coincide with the days that our average river temperature series breaches the 25°C threshold. The likelihood of an individual river exceeding 25°C given that the average series does, is very high (0.993). These exercises illustrate the close correspondence between the individual temperature trends and the aggregated measure of critical river temperature that we have constructed.

The correlation coefficients for the individual river levels are less pronounced but are still highly significant. To provide a more formal test of the disaggregated river level effects though, we incorporate data from each of the individual rivers separately into the regression analysis. More precisely, we run four new regressions based on the specifications of Model 2, each time replacing the average river level series with data from a single river. These results are presented in Table 2. As can be seen from the table, the individual river level coefficients are all negative and thus in-

[23] While none of the results from the alternate specifications are reported here, they are available from the authors upon request.

[24] The formulas used are $F(t) = \sin(2\pi t/365)$ and $G(t) = cos(2\pi t/365)$, respectively, where t denotes time in days. This reflects the fact that a full seasonal cycle would complete once a year.

[25] We have also included a log-transformed, 90-day MA of CO_2 future contracts as a proxy for the input costs of thermal-based electricity production. While we have available data only for the period 2006–2009, the basic results of our regression analysis are not altered by the inclusion of this CO_2 permit variable.

[26] Müller, Greis, and Rothstein (2007) include information about shutdown dates over the period July 19–31, 2006, based on secondary sources, such as newspaper and other media articles. Such data are likely to be incomplete and imprecise and should therefore be used with great care.

[27] The aggregate 25°C threshold that we have defined does gloss over some river- and site-specific issues. The permitted mixing temperature from the thermal discharge in Germany varies between 23°C and 28°C (Müller, Greis, and Rothstein 2007). Our choice of 25°C is based on a careful reading of the literature, as well as some initial testing of different thresholds.

[28] These series are detrended using the set of month and year dummies.

TABLE 2
Individual River Levels, Dependent Variable = Price (€/MWh)

	Elbe	Main	Neckar	Rhine
Coefficients				
Base volume	8.099*** (1.004)	8.256*** (1.020)	8.081*** (0.982)	8.277*** (1.029)
Predetermined Variables				
L1.Base price	0.644*** (0.053)	0.633*** (0.053)	0.623*** (0.053)	0.620*** (0.055)
L7.Base price	0.158** (0.054)	0.153*** (0.053)	0.168*** (0.053)	0.140*** (0.054)
L1.Base volume	− 3.738*** (0.464)	− 3.757*** (0.460)	− 3.672*** (0.447)	− 3.749*** (0.472)
L7.Base volume	− 2.230*** (0.374)	− 2.330*** (0.368)	− 2.271*** (0.360)	− 2.284*** (0.379)
River levels (cm)				
Single series	− 0.130 (0.074)	− 0.372** (0.171)	− 0.511*** (0.142)	− 0.217*** (0.074)
River temperature (°C)				
D^{Riv25} (1 = RT > 25°C)	− 0.025 (0.073)	0.003 (0.074)	0.004 (0.074)	− 0.068 (0.075)
$RT - 25$°C, if > 25°C	0.208*** (0.030)	0.222*** (0.028)	0.227*** (0.028)	0.210*** (0.028)
Brent (90-day MA)	0.131 (0.194)	0.113 (0.189)	0.0755 (0.191)	0.137 (0.205)
Tests				
Endogeneity test[a]	478.40***	431.99***	442.59***	448.29***
1SLS instrument joint significance test	36.78***	36.67***	37.14***	36.63***
Instrument relevance test[b]	22.74***	24.55***	23.26***	29.37***
Overidentifying restrictions test[c]	5.27	5.78	5.58	5.23
Autocorrelation test[d]	4.27**	3.38	4.24**	2.75
Joint significance tests (χ^2)				
Month dummies	35.25***	36.04***	37.95***	36.89***
Year dummies	39.31***	38.95***	43.02***	42.16***
N	2,915	2,915	2,915	2,915

Note: Based on Model 2 in Table 1. For each regression, the average river level series from Model 2 have been replaced with level data from an individual river. All other coefficients are excluded.
[a, b, c, d] See Table 1 for interpretation.
** $p < 0.05$, *** $p < 0.01$.

dicative of a higher electricity price when river levels fall. That is not to say that they all have the same marginal impact, although this is perhaps not surprising given that the importance of these rivers in terms of providing cooling water to Germany's thermal industry can vary quite substantially.[29]

In sum, we believe that these results serve to emphasis the validity of our predominantly aggregate approach. Again, the purpose of this paper is to test for systematic vulnerabilities, and we would argue that focusing too much on individual trends and measurements actually distracts from the wider climate and its associated risks. The real danger implicit in climate change, for example, is that *mean* values are pushed closer to their regulatory thresholds, such that widespread capacity reductions become more commonplace. It therefore seems most appropriate to focus on the "average" effect, since this captures the systemic risk that comes when rivers all across the country are breeching their regulatory thresholds at the same time.

V. CONCLUDING REMARKS

This paper has sought to quantify how electricity prices are impacted by the availability of cooling water. Our analysis is primarily motivated by the fact that water plays a critical role in the thermal production cycle, where tremendous volumes of freshwater are drawn every day to serve the cooling needs of thermal-based power plants around the world. At the same time, these water sources are subject to environmental regulations, competing economic concerns, and periods of relative scarcity.

[29] As expected, the other coefficients are extremely similar across the four different models.

We have argued that Germany serves as a good case study to investigate these issues, and have based our analysis on daily data taken over a period of seven years. Having successfully controlled for various demand effects within a 2SLS regression framework, our results indicate that electricity prices are significantly affected by both falling river levels and higher river temperatures. The magnitude of these relationships varies according to the exact specifications of the regression model at hand, and we have explored several contemporaneous and dynamic settings. Qualitatively, however, they all tell a very similar story: electricity prices are driven higher by falling river levels and higher river temperatures. Under a fully contemporaneous setting, the electricity price is expected to rise by around 1% for every 1% that river levels fall. The dynamic specification, on the other hand, suggests that the price will rise at about half that rate in the short run, before increasing to approximately 1.5% in the long run. With regard to river temperatures, the models imply that the price of electricity will increase by roughly 1% for every degree that temperatures rise above a 25°C threshold. Incorporating the longer-run effects implied by a dynamic model shows that prices will rise by nearly 4% over the course of a week. In addition to this slope effect, we test for a price discontinuity on either side of this 25°C threshold. However, we do not find evidence of a marked price jump once the threshold is breached. An explanation, which is consistent with our theoretical model and the surveyed literature, is that power plants reduce their output in stages rather than simply shutting down. This allows them some additional scope for managing thermal pollution, although a decrease in output—and hence increase in price—cannot be fully avoided.

One implication of our findings is that future climate change will impact electricity prices not only through changes in demand, but also as a result of increased cooling water scarcity. We believe that this type of analysis would lend itself to applications in a number of regions and countries, all of which are marked by a pronounced dependency on thermal-based power, at the same time as being prone to drought and periodic heat waves.

APPENDIX

The Effect of Changes of River Temperature, *T*, on Optimal Quantity, *Q**, and Price, *p**

We start from our first-order condition,

$$p^*\left(1-\frac{1}{\varepsilon}\right)=\frac{\partial c(Q^*)}{\partial Q}+p_{\mathrm{W}}(RL)\cdot\frac{1}{A(T_{\mathrm{EW}}-T)}+\lambda\cdot\frac{1}{S\cdot A(T_{\mathrm{EW}}-T)}\cdot(T_{\mathrm{EW}}-T),$$

and want to find the effect of a river-level temperature increase on the prices. Using standard comparative statics we define the problem as follows (e.g., Dixit 1976, ch. 8):

$$\frac{dQ}{dT}=-\frac{\partial G(Q,T)/\partial T}{\partial G(Q,T)/\partial Q}$$

where

$$\begin{aligned}G(Q,T)&=\frac{W}{S}\cdot T_{\mathrm{EW}}+\frac{S-W}{S}\cdot T\\&=\frac{W}{S}\cdot(T_{\mathrm{EW}}-T)+1\\&=\frac{Q}{S\cdot A(\cdot)}\cdot(T_{\mathrm{EW}}-T)+1,\end{aligned}$$

which is the left-hand side of the constraint $G(Q,T)\le\overline{T}$. We have that

$$\frac{\partial G(\cdot)}{\partial Q}=\frac{T_{\mathrm{EW}}-T}{S\cdot A(\cdot)}>0$$

and

$$\begin{aligned}\frac{\partial G(\cdot)}{\partial T}&=\frac{Q}{S}\left[\frac{A'(\cdot)\cdot(T_{\mathrm{EW}}-T)-A(\cdot)}{A(\cdot)^2}\right]+1\\&=\frac{A(\cdot)\cdot W}{S}\cdot\left[\frac{A'(\cdot)\cdot(T_{\mathrm{EW}}-T)-A(\cdot)}{A(\cdot)^2}\right]+1\\&=\frac{1}{A(\cdot)}\cdot\left\{\frac{W}{S}\cdot[A'(\cdot)\cdot(T_{\mathrm{EW}}-T)-A(\cdot)]+A(\cdot)\right\}\\&=\frac{1}{A(\cdot)}\cdot\left\{\frac{S-W}{S}\cdot A(\cdot)+A'(\cdot)\cdot(T_{\mathrm{EW}}-T)\right\}>0,\end{aligned}$$

as long as $A'(\cdot) > 0$ (and $T_{EW} > T$). That means that $dQ/dT < 0$. This is an inward shift of the supply curve. With a given demand, and assuming that the supply curve is not completely flat, a rise in temperature will lead to increased prices.

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