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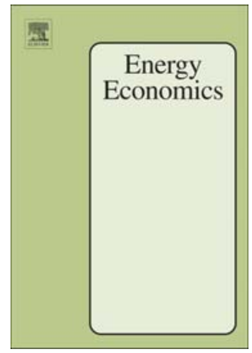

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Adaptation of Thermal Power Plants: the (Ir)relevance of Climate (Change) Information.☆

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Abstract

When does climate change information lead to adaptation? We analyze thermal power plant adaptation by means of investing in water-saving (cooling) technology to prevent a decrease in plant efficiency and load reduction. A comprehensive power plant investment model, forced with downscaled climate and hydrological projections, is then numerically solved to analyze the adaptation decisions of a selection of real power plants. We find that operators that base their decisions on current climatic conditions are likely to make identical choices and perform just as well as operators that are fully 'informed' about climate change. Where electricity supply is mainly generated by thermal power plants, heat waves, droughts and low river flow may impact electricity supply for decades to come.

Keywords: Thermal Power Plants, Climate Change, Adaptation, Real Options
JEL: D8, Q40, Q51, Q53, Q54

1. Introduction

1.1. Problem and question

In the United States more than 85% of all electricity is generated from nuclear and fossil fuels (e.g., coal, natural gas) in thermal power plants (EIA, 2015). At 75%, the European Union exhibits a significant dependence on this type of electricity production too (Eurostat, 2013). Many thermal power plants depend on a river for their cooling water. As such, these plants may experience forced load reductions or shut downs during heat waves or droughts. This is due to sheer lack of water, or due to environmental regulations that limit waste-heat discharges from power plants to prevent excessive river warming. The effects of two European heat waves in 2003 and 2006, during which several power plants in France and Germany were forced to reduce production or even had to shut down temporarily, have been well documented (see Kopytko and Perkins (2011), Rubbelke and Vogele (2011) and Pechan and Eisenack (2014)). Cooling water is indeed "a critical resource in the thermoelectric power industry" (Feeley III et al., 2008).

No matter the extent and speed of mitigation, some degree of climate change over the course of this century seems inevitable (IPCC, 2014). Melting of glaciers will impact river runoff worldwide (IPCC, 2014), shifting rivers to become dominantly precipitation-fed. Secure cooling water supply, the life-line for thermal power plants, may no longer be a given. Indeed, van Vliet et al. (2012b) have shown that increases in river water temperature and decreases in summer river flow in Europe and the United States are to be expected, and subsequently find that in these regions the probability of extreme

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reductions (> 90%) in thermal electricity generation will on average increase by a factor three over the period 2031-2060.

Climate vulnerability of thermal power plants begs the question what type of behavioral changes or investments are to be expected from agents in the electricity sector, and whether these can substantially limit damages from environmental change? As thermal power plants represent large, capital-intensive installations with a technical (and economic) lifespan that often exceeds 40 years, we argue that a-priori there appears to be a strong rationale for operators to maximize profits by seeking information on climate change, that is, by acquiring and using projections of future climatic conditions. For thermal power plants these projections would naturally include information on relevant ambient variables, such as water temperature. This brings us to the central question of our paper: when plant operators decide on adaptation, does climate change information make a difference?

To answer our main questions, we construct a dynamic investment model that rests on real options analysis and incorporates thermodynamic principles, elements from hydrology and power plant engineering knowledge. In the short run, operators adapt in response to (changes in) weather conditions by choosing their inputs of production, that is, fuel consumption, cooling water flow and cooling water discharge temperature, in order to maximize plant profits. In the long run, under anticipation of (some degree) of climate change, operators decide on the optimal timing to retrofit the existing power plant with a more water efficient cooling technology. Similarly, after the plant retires, investors decide on the cooling technology of the new plant to be built in order to maximize plant value.

In the first part of the paper we use a number of simple frameworks, "models of our model", to illuminate the relationship between plant value, climate change information and adaptation. We show that there are fewer cases for which climate change information will increase operator profits when (i) adaptation investments also bring substantial non-climate related gains or costs, so-called no-regret benefits or no-regret costs, and when operators (ii) are faced with uncertainty over electricity prices.

In the second part of the paper we apply our main model to two real-world power plants, a nuclear plant in France and a coal-fired power plant in the United States. Here we make use of simulations of water temperature and river flow for the period 2011-2080. Our point of departure are the recent Representative Concentration Pathway (RCP) 2.6 and 8.5 scenarios, which offer the widest possible range of emissions scenarios (see Moss et al. (2010)). In this paper, the simulations that are based on the RCP2.6 and RCP8.5 scenarios are synonymous with climate change (information), whereas we refer to simulations of the recent past (1971-2000) as (information on) the status quo or current climate.

The main results emerging from our empirical application are as follows. For one, the net losses from climate change are small, averaging at approximately 1% of net operating profits. Part of the intuition here is that the gross losses from climate change, that is, the losses that are obtained by an ignorant operator who does not forecast, appear to be a fairly small fraction of net operating profits to begin with, which reflects the remarkable flexibility of current power plant technology to adjust to adverse day-to-day changes in ambient conditions during spring, fall and winter.

Moreover, for two different power plant case studies we show that operators that base their decisions on current climate conditions are likely to make identical choices and perform just as well as operators that are 'fully' informed about future climatic conditions. The main reasons underlying this core result are twofold. First of all, there are substantial no-regret benefits from investing in advanced cooling technologies under current climate conditions. On top of that, the additional climate damages occurring under the RCP2.6 and RCP8.5 scenarios relative to the status quo scenario appear to be relatively small. This implies that the range of investment conditions for which an adaptation threshold is tipped when climate change information is available, but not without this information, is rather small. Second, under price uncertainty postponing adaptation becomes more attractive. In that case, the marginal value for operators of having a climate scenario that is 'closer' to the true scenario becomes smaller.

Making projections of future climatic conditions is difficult and costly because of substantial climate change uncertainty. One wonders how valuable such information is in the first place. By considering a wide range of climate change scenarios, including the high RCP8.5 scenario, we have made a strong case for promoting adaptation by means of projecting future climatic conditions. Since the added value of climate change information for our selection of power plants seems to be small, it appears that the costs that climate change uncertainty imposes on forward-looking operators are manageable. This result may be relevant for other agents vulnerable to climate change too, in particular for those encountering significant price uncertainty and whose adaptation options are characterized by substantial no-regrets benefits or no-regret costs.

Our paper relates to a number of strands of literature. In the energy-water nexus, an increasing number of scholars have described and analyzed the vulnerability of thermal power plants to low river flows and high air and water temperatures (see Arrieta and Lora (2005), Koch and Vogele (2009), Rubbelke and Vogele (2011), Linnerud et al. (2011), Förster and Lilliestam (2010), Golombek et al. (2011), McDermott and Nilsen (2014), Schaeffer et al. (2012), van Vliet et al. (2012b)). In contrast to these papers, (i) we are more explicit about the means by which power plants can adapt to climate change and (ii) we explain how the (in)correct projections of future climatic conditions affect operator's decisions and the impact from climate change.

Koch and Vogele (2009) noted that while low river flows directly diminish cooling water availability, high air temperatures tend to decrease plant efficiency, which increases the production of waste heat and subsequently raises the demand for cooling water. Based on analysis of both plant-specific data and panel data for a set of countries, Linnerud et al. (2011) conclude that a 1°C rise in ambient temperature will reduce electricity output by 0.4-0.7% at low temperatures (*efficiency effect*) and by about 2.3% at high temperatures, as physical and environmental constraints become binding (*load reduction effect*).[1]

A number of studies have looked at the effects of forced load reductions at a more aggregate level of analysis. Rubbelke and Vogele (2011) employ the same water demand model as Koch and Vogele (2009) to analyze the effects of climate change on the exchange of electricity between European countries. They find that when nuclear plants in France, Switzerland and Spain have to reduce their production during episodes of drought, an import-dependent country like Italy may then have difficulties to meet its electricity demand.[2] Pechan and Eisenack (2014) construct a simulation model of the German electricity wholesale market to study the impact of the German heat wave of July 2006. Their simulations show that forced capacity reductions at coal-fired and nuclear power plants increased prices on average by 11%.

A study by McDermott and Nilsen (2014) confirms that low river flow and high river water temperatures can have significant effects on aggregate electricity prices. In their empirical study of German electricity prices over the period 2002-2009, they find that the price of electricity increases by roughly 1-1.5 (4) percent in the short (long) run when water temperature increases by 1 degree Celsius.[3] Their analysis also suggests a threshold effect, with prices rising more sharply in very hot periods ($T > 25°C$).

In terms of methodology, our paper relates to a large literature on adaptation to climate change in the agricultural and forestry sectors (see Mendelsohn et al. (1994), Plantinga (1998), Smith et al. (2000), Insley (2002), Sedjo (2010), Guo and Costello (2013)). Similar to these contributions, we present climate change impact estimates that are affected by adaptation opportunities. With the exception of Guo and

[1]Similarly, in their theoretical analysis of a pressurized water reactor nuclear power plant, Durmayaz and Sogut (2006) find that a 1 °C rise in ambient temperature reduces efficiency and production by 0.12% and 0.45%.

[2]Klein et al. (2013) show that in Europe Luxembourg and Greece are most susceptible to climate change, because they source their power from climate-affected sources.

[3]The short run refers to the immediate effects of changes in hydrological conditions, whereas the long run is used to indicate the effects over the course of a week.

Costello (2013), however, none of these studies highlight the relative value of the different margins of adaptation that are available. We apply an accounting methodology similar to theirs to asses the value provided by short-run and long-run adaptation options. Interestingly, in our case the need for adaptation derives from the joint restrictions imposed on production by both climate change and local environmental regulations. In contrast to Guo and Costello (2013), we find that short-run adaptation is more valuable compared to long-run adaptation, which owns to the flexibility of the existing power plant technology and the relatively large investment costs associated with long-run adaptation.

The rest of this paper is structured as follows. In Section 2 we use a number of simple analytical models to analyze a power plant's short-run and long-run adaptation options and to explain under what conditions climate change information is relevant and triggers adaptation. Building on these insights, we then construct a more general dynamic investment model in Section 3 that we apply to two representative power plants. Here we also present the model's parameter values and projections of future climate and hydrological conditions. For each of our two power plants, we quantitatively illustrate the importance of climate change information in Section 4 by calculating the difference in operating profits between an informed and an (semi-)ignorant operator. Section 5 concludes.

2. Power Plants and Adaptation to Climate Change

Figure 1 illustrates the geographic distribution of the 300 largest power plants in Europe.[4] Each of these plants depends on cooling water availability and ambient temperatures for their operation. As climate change is likely to affect these ambient conditions, it represents yet another source of uncertainty that operators must deal with, relevant not only while navigating the fuel, electricity and CO_2 markets, but also when deciding on development of, investment in or dismantlement of their plants.

Against this background, we consider the problem of a power plant operator, who maximizes discounted lifetime profits from electricity production. She can adjust production along two decision margins. In the short-run she can adapt to ambient conditions using technology embodied in the existing power plant. In the long-run she can retrofit the plant with new technology (e.g., a supplementary cooling tower) to cope with adverse ambient conditions and to maintain capacity of her plant.

Given the operator's problem, the main question posed here is whether information on climate change will induce any adjustments along these two margins. In other words, under what conditions is climate change information relevant for a power plant operator? By separately analyzing the two main channels via which operators can adapt, we will first provide a qualitative answer to this question.

2.1. Power plant adaptation in the short run

2.1.1. A simple model

To capture the relationship between fresh water availability, water temperature and electricity generation, we set-up a simple production function for a thermal power station. Power stations liberate heat Q from primary energy fuels (e.g., coal, natural gas, biomass and uranium) with energy content e, that is, $Q = e$, and convert that heat into electricity y and waste heat Q_w (all in MJ/s or MW) via a steam turbine and generator:

$$Q = y + Q_w \tag{1}$$

Note that without further assumptions, eq. (1) is just an identity. According to the Second Law of Thermodynamics (see the supplementary appendix) only a fraction η of the heat Q is converted into

[4]The 300 largest power plants are selected on the basis of their actual production in the year 2010. Source: `http://enipedia.tudelft.nl/wiki/Europe/Powerplants,accessedMarch1,2015`

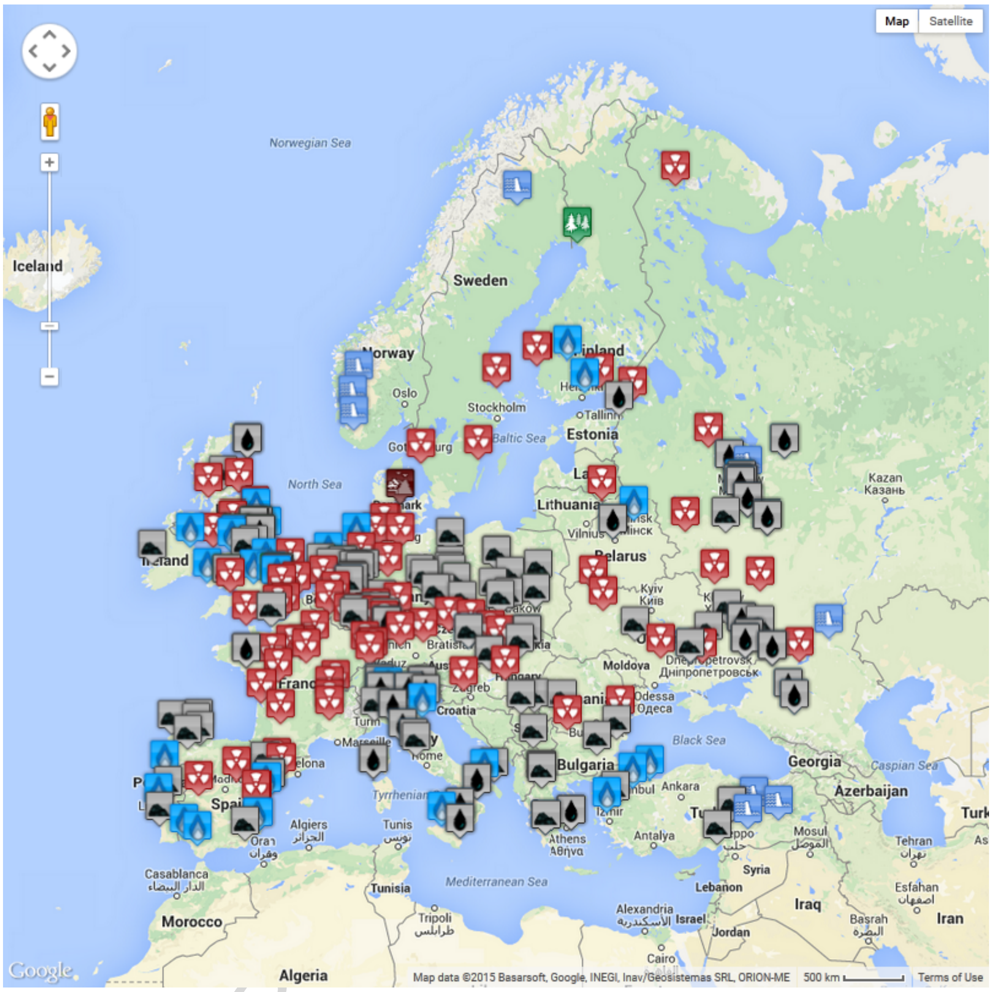


Figure 1: Largest 300 thermal power plants in Europe.

useful work, that is, electricity y. Therefore $y = \eta \cdot e$ and $Q_w = (1 - \eta) \cdot e$. Plant efficiency η is assumed to be linearly decreasing in water intake temperature T [Kelvin],

$$\eta = \eta_D - \delta \cdot (T - T_D) \tag{2}$$

where $\delta > 0$ is the sensitivity of plant efficiency to temperature, while T_D and η_D represent respectively the mean temperature and efficiency that were expected at the time engineers designed the plant. Fuel consumption and output are bounded from above,

$$e \leq \bar{e} \tag{3}$$

$$y \leq k \ , \ \ k \equiv \eta_D \bar{e} \ , \tag{4}$$

where k is defined as the maximum plant output, or nameplate capacity, that is attained when fuel consumption is maximized and $T = T_D$. If water intake temperature is below design we note that $\eta > \eta_D$ and the plant's output will then be capped at nameplate capacity with the intake of fuel below its maximum. When the actual water intake temperature exceeds the design temperature the plant operates at an efficiency below design, $\eta < \eta_D$, and output falls short of nameplate capacity.

Let $y_d \equiv 24 \cdot 10^{-3} \cdot y$ be daily electricity production [GWh], such that daily operating profits π equal revenues from electricity production minus costs,

$$\pi = \left(p - \frac{c}{\eta}\right) y_d \tag{5}$$

where p is the price of electricity, and c and $\frac{c}{\eta}$ are respectively the gross and net marginal energy cost of production (all in \$/GWh). In direct cooling, the heat absorbed Q_w [MJ/s], the cooling water temperature increase ΔT and flow l [m^3/s] are related via the following equation:

$$Q_w = \frac{l\Delta T}{\xi}, \tag{6}$$

where ξ equal is a correction factor accounting for various aspects of the relevant cooling technology (see the appendix). All things equal, a power plant with a closed-cycle (C-C) cooling tower system will require less environmental resources than one with a once-through (O-T) cooling system, that is, $\xi_{OT} < \xi_{CC}$.

The firm selects inputs l and ΔT in order to dispose off the total supply of waste heat. Its input selection is subject to limitations. First, regulation imposes restrictions on both the maximum permissible temperature $T_{\max}$ and on the $\Delta T_{\max}$ of the coolant,

$$\Delta T \leq \min(T_{\max} - T, \Delta T_{\max}) \equiv \overline{h} \tag{7}$$

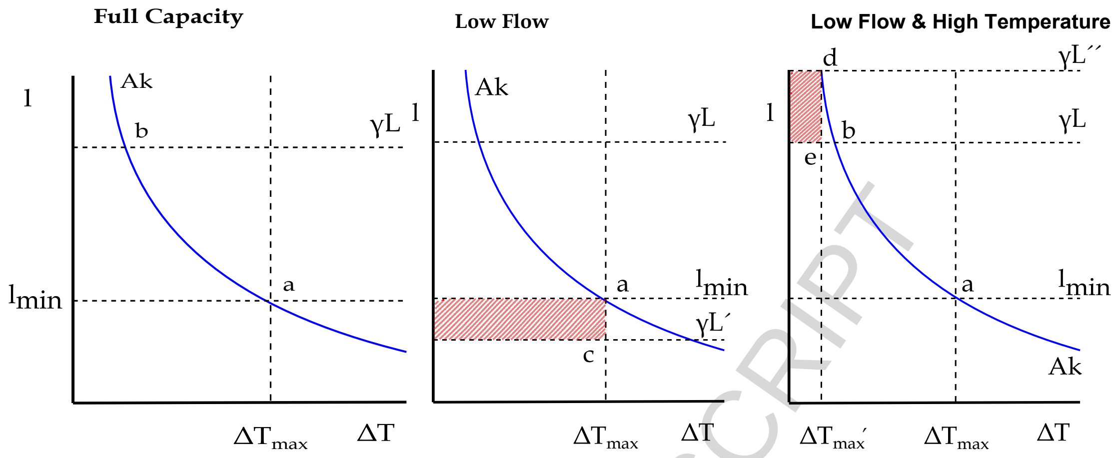
where $\overline{h}$ is a mnemonic for "maximum *h*eating". Thus, from eq. (6) and (7) we learn that a higher ambient (water or air) temperature ceteris paribus leads to a higher cooling water flow (*demand effect*). Second, let us refer to L [m^3/s] and γ respectively as the local river discharge volume and the maximum allowed (or technically feasible) share of river water that can be used for thermal cooling. Since water demand can not exceed supply,

$$l \leq \bar{l} \equiv \gamma L \tag{8}$$

Note that the product $\overline{hl}$ can be interpreted as 'waste heat removal capacity'.[5] On a daily basis, a power plant manager maximizes power plant profits (5) by choosing fuel amount e, cooling water flow l and ΔT, subject to constraints on fuel intake (3), production capacity (4), cooling water temperature (7) and water intake (8). In the appendix we show that this optimization problem with multiple choice variables can be transformed into an optimization problem with one single variable, the cooling water inflow l. So how exactly does the operator adapt in the short-run?

Proposition 1-A. Power plant adaptation in the short-run.
When water temperature increases, a power plant operator can maintain maximum production capacity by increasing water intake, despite plant efficiency loss (efficiency reduction effect). Environmental regulations, plant design characteristics and low river flow levels are all factors that limit the use of this short-run adaptive measure, so that at some point production must diminish (load reduction effect). The operator may also halt production when fuel costs exceed electricity revenue.
Proof. Appendix B.1.

[5]Third, some countries effectively limit the amount of heat discharged into the natural environment. Such constraints on thermal pollution typically specifies restrictions regarding the length and temperature of the heat plume at various distances from the point of immission. Here we abstract from thermal pollution considerations because (i) we lack the information to incorporate this constraint into our empirical applications and (ii) because the temperature restriction on the coolant serves a very similar purpose.



(a) Production at full capacity

(b) Load reduction

Figure 2: Power plant production isoquant

To illustrate the workings of the load reduction effect, we turn to a graphical analysis of input selection by a thermal power plant.[6] Using eqs. (1), (4), (6) and $Q_w = (1-\eta) \cdot e$, we can write the gross demand for cooling ξQ_w as a function of the plant's production capacity, that is, $\xi Q_w = Ak$, where the parameter bundle $A \equiv \xi \frac{1-\eta}{\eta}$ is a measure of the plant's cooling intensity. The blue line in figure (2a) then represents a production isoquant; all combinations of water inflow and temperature increase for which the firm produces at full capacity. The line segment between a and b represents all *feasible* combinations of inputs. At a, the inflow of cooling water is minimized and the increase in cooling water temperature is at its maximum. At b the firm uses the maximum possible intake of water, limited either by natural constraints or technical constraints, thereby minimizing the increase in cooling water temperature.[7]

In figure (2b) we display a situation where low river flow ($\gamma L' < \gamma L$) reduces the maximum possible intake of cooling water. Since it is impossible to increase cooling water temperature beyond $\Delta T_{\max}$, capacity is restricted at c. Similarly, load reduction can also take place when surface water temperature is high, such that the permissible increase in cooling water temperature is limited to $\Delta T'_{\max} < \Delta T_{\max}$ (see figure (2b)). In this case, the intake of cooling water would have to increases to point d on the production isoquant, but the required level of river discharge, $\gamma L'' > \gamma L$, is unavailable and therefore maximum production coincides with the selection of 'inputs' at point e. Since point e is situated below the blue isoquant, electricity production no longer takes place at full capacity. The shaded areas in both figures represent the total loss of output due to hydrological constraints (up to a scaling factor).

2.1.2. Weather and forward markets

We have implicitly assumed that the power plant only participates in a spot (or day-ahead) market, in which the lag between the decision to sell and the decision to produce is minimal. In reality, plant operators may want to participate in forward markets too. Here a sale may take place days, weeks or even months in advance of delivery. When selling electricity on a forward market, weather conditions and hence available production capacity on the date of delivery are unknown to the operator. Weather uncertainty is not necessarily an issue if the forward market is purely financial. In that case, a commit-

[6]For simplicity, we abstract here from the efficiency effect, i.e., $\delta = 0$ so that $\eta = \eta_D$ (see eq.(2)).

[7]For simplicity, we assume that the costs of the intake of water are independent of the level of the flow. This implies that the costs of pumping water are part of the plant's fixed costs, leaving operating profits (5) unaltered. McDermott and Nilsen (2014) assume that the costs of pumping water are 'substantial enough' to model them. However, since the marginal costs of pumping water are likely to be small compared to other costs (e.g., fuels, capital costs, labor), this assumption does not affect our results.

ment made in the forward market can be undone by buying the required electricity on the spot (or the day-ahead) market.

In some cases, the independent system operator (ISO) may impose a penalty if the actual level of electricity generated on the date of delivery falls short of the commitment made in the forward market (Bushnell and Wolak, 2006). To analyze the impact of weather uncertainty on power plant sales and profits in this context, we set-up a model in which a risk-neutral firm faces different (expected) prices in the forward and spot (or the day-ahead) markets, and decides on how much electricity to commit via the forward market at a time when future production capacity is still unknown, for example due to weather uncertainty. Let us refer to p_1, p_2, y_C, y_S, k and k_L as respectively the net forward market price, the net spot market price, the amount of electricity committed via the forward market, the amount of electricity sold on the spot market, the maximum production capacity and the production capacity in a state of bad weather.[8] The amount of electricity sold (or bought) on the spot market equals the difference between the available production capacity and the committed amount of electricity in the forward market, that is, $y_S = k - y_C$ and $y_S = k_L - y_C$ in the good and bad state respectively.

The power plant pays a penalty if its commitment falls short of its produce. Let $f \geq 0$ be the per unit fee that is imposed by the ISO on power plants that break their commitment and let q and $1-q$ be the probability of a good and bad weather state respectively. Expected profits then read:

$$E\left[\pi(y_C)\right] = \left\{ \begin{array}{ll} p_1 y_C + q p_2 (k - y_C) + (1-q) p_2 (k_L - y_C) & , \; y_C \leq k_L \\ p_1 y_C + q p_2 (k - y_C) - (1-q)(p_2 + f)(y_C - k_L) & , \; k_L \leq y_C \leq k \end{array} \right\} \tag{9}$$

Since this profit function is linear in y_C, three (corner) solutions immediately suggest itself, that is, y_C^* is equal to 0, k_L or k. Let us refer to k and k_L as variables that are "weather" related, q as related to "weather uncertainty", and $k^e \equiv qk + (1-q)k_L$, i.e., average production capacity, as a "climate" variable. We can then summarize the relationship between weather, climate and adaptation in the following proposition.

Proposition 1-B. Power plant adaptation in the short-run: the role of weather and climate.
(i) *In equilibrium the power plant sells either nothing, an amount equal to the minimum production capacity, or an amount equal to the maximum production capacity on the forward market, that is,*

$$y_C^* = \left\{ \begin{array}{ll} 0 & , \; p_1 - p_2 < 0 \\ k_L & , \; 0 < p_1 - p_2 \leq (1-q)f \\ k & , \; 0 < (1-q)f < p_1 - p_2 \end{array} \right\} \tag{10}$$

(ii) *Weather affects expected profits if and only if the operator faces a positive risk premium, that is, $p_1 - p_2 > 0$, otherwise expected profits depend only on climate.* (iii) *If the expected penalty outweighs the risk premium, the operator adapts by selling only the minimum available production capacity on the forward market.*
Proof. (i) Substituting for the three candidate solutions into eq. (9) and rearranging terms, we get:

$$E\left[\pi(y_C)\right] = \left\{ \begin{array}{ll} p_2 k^e & , \; y_C = 0 \\ p_2 k^e + (p_1 - p_2) k_L & , \; y_C = k_L \\ p_2 k^e + (p_1 - p_2) k - (1-q) f (k - k_L) & , \; y_C = k \end{array} \right\} \tag{11}$$

The solution in eq. (10) then follows from comparing the three expressions in eq. (11), e.g., $E\left[\pi(0)\right]$ is

[8] Our model can cope with complications resulting from increased deployment of renewable energy. The intermittency of wind and solar implies that spot market prices may become more volatile, which is irrelevant provided the average price p_2 stays constant, or it may force thermal power plants to reduce their output on a very windy or sunny day. The latter effect can be captured by a reduction of k_L.

greater than $E[\pi(k)]$ and $E[\pi(k_L)]$ iff $p_1 - p_2 < 0$. (ii) Inspecting eq. (11), and taking note of the equilibrium conditions in eq. (10), we observe that k_L, k and/or q are only relevant when $p_1 - p_2 > 0$. (iii) Starting from $0 < (1-q)f < p_1 - p_2$, we note that if q decreases sufficiently, such that $0 < p_1 - p_2 \leq (1-q)f$, the operator switches from selling a quantity k on the forward market to selling a quantity k_L on the forward market. ■

If the risk premium is negative operators sell their entire output on the spot market. As a result, expected profits depend on climate (via k^e), but not on weather. If the risk premium is positive, however, operators will sell at least some of their output on the forward market and weather uncertainty indirectly reduces profits via the penalty mechanism. Assuming $0 < (1-q)f < p_1 - p_2$, an increase in the probability of bad weather increases the probability of paying a penalty. Expected profits fall. Once the expected penalty outweighs the risk premium, the firm will only sell the minimum available amount of electricity, k_L, on the forward market. Hence, the loss in profits that the firm incurs from weather uncertainty is then bounded from above by the ability to adapt.

Proposition 1-B highlights the conditions under which weather (uncertainty) and climate influence plant decisions and profits. Our model is deliberately simple. It abstracts from many factors that may be relevant in practice, including risk aversion and market power in forward markets (see Allaz and Vila (1993)). We have also abstracted from the predictability of weather itself. A more elaborate model would have to specify probability distribution functions for weather, explain how plant operators learn from weather observations, and how they make weather forecasts. In the rest of this paper we will abstract from considerations related to weather. In practice, penalties are likely to be small, ISOs may want to accommodate for 'legitimate' weather-related errors in capacity forecasting by plant operators, and risk premia may often be absent.[9]

2.2. Power plant adaptation in the long run

Forward looking operators can also invest in new (cooling) technology to adapt to climate change. To analyze how climate information can trigger this irreversible investment decision, we present two analytically tractable models (Appendix B.2), "models of the model", each of which highlights a set of parameters crucial to shaping operator's decisions.

2.2.1. A deterministic model

Consider a power plant with per-period profits $p_t k_t$, where p_t and k_t represent respectively the price of electricity and the usable capacity over period t, $t \in [t_0, t_1]$. The remaining lifespan of the power plant equals $t_1 - t_0$. We examine a situation where at some known future date $t_C > t_0$ climate change permanently reduces usable plant capacity from k_0 to k_C, with $k_0 > k_C$.[10]

The operator can retrofit the existing power plant by investing in additional cooling capacity at cost I. For simplicity, the retrofit is assumed to make the plant 'immune' to climate change, providing the

[9] In our empirical application of section 4 we allow electricity prices to grow at different rates. This indirectly captures the main effect of weather uncertainty that we explored here, which is that weather uncertainty induces operators to sell their electricity at relatively low prices on spot (or day-ahead) markets.

[10] This loss of production capacity can be rationalized as follows. If an ambient variable l (e.g., air temperature, river flow level, river temperature) falls short of a threshold level $\bar{l}$, capacity is reduced below its maximum capacity, that is, $k(l) = k_A$ for $l \geq \bar{l}$ and $k = k(l) < k_A$ for $l < \bar{l}$ with $k'(l) \geq 0$. Let $f(l)$ be the probability density function of l with support $[l_0, \infty)$ such that expected capacity at any given time is given by:

$$k = \int_{l_0}^{\infty} k(l) f(l) dl \tag{12}$$

A climate change induced shift of $f(l)$ will permanently reduce the expected usable capacity of the power plant from k_0 to k_C, with $k_C < k_0$. Suppose l is drawn from e.g., a normal distribution or uniform distribution, then one can write $f(l) = f(l; \mu_l, \sigma_l^2)$ with mean μ_l and variance σ_l^2. It then follows immediately that, due to the non-linearity of the production function, a variance induced shift has ceteris paribus a larger impact than a mean induced shift.

plant with a constant production capacity $k_A > k_C$ till the end of its technical lifespan at t_1. In practice, a retrofit may serve additional purposes. In that case, it may carry costs or benefits that are accrued independent of climate change. For instance, when a plant is taken offline to retrofit its cooling system, the operator may decide to also upgrade the plant with an additional generator ($k_A > k_0 > k_C$). In contrast, when a retrofit also implements carbon capture and storage (CCS) technology, plant efficiency is reduced and ex-post capacity will fall short of the initial capacity ($k_0 \geq k_A > k_C$). We refer to these cases as ”no-regret benefits and costs” respectively.

The price of electricity is assumed to grow at a constant rate g_p. Let r be the annual discount rate. Then the net present value of the power plant with adaptation initiated at time t_A is

$$\Pi(t_A, t_1) = \left\{ \begin{array}{ll} \int_{t_0}^{t_C} p_t k_0 e^{-r(t-t_0)} dt + \int_{t_C}^{t_1} p_t k_C e^{-r(t-t_0)} dt & , \text{ never adapt.} \\ \int_{t_0}^{t_A} p_t k_0 e^{-r(t-t_0)} dt + \int_{t_A}^{t_1} p_t k_A e^{-r(t-t_0)} dt - e^{-r(t_A-t_0)} I & , \ t_A \in [t_0, t_C) \\ \int_{t_0}^{t_C} p_t k_0 e^{-r(t-t_0)} dt + \int_{t_C}^{t_A} p_t k_C e^{-r(t-t_0)} dt + \int_{t_A}^{t_1} p_t k_A e^{-r(t-t_0)} dt - e^{-r(t_A-t_0)} I & , \ t_A \in [t_C, t_1) \end{array} \right\} \tag{13}$$

Let us differentiate between an informed operator and ignorant operator; whereas the first is fully aware of the timing and magnitude of the impact of climate change, the latter is not. As we show formally in the appendix, an informed operator will adapt once the net annual benefits from being endowed with additional production capacity $\Delta k \equiv k_A - k_C$ equal the cost of capital, $p_{t_A^*} \Delta k = rI$ (first-order condition), which implicitly defines the optimal time t_A^*, and if there is sufficient time to recoup the investment, such that the impact on the plant's net present value is positive, $\Delta\Pi(t_A^*, t_1) \geq 0$ (NPV condition). Otherwise, she never adapts. An ignorant operator might only adapt if her decision carries no-regret benefits.

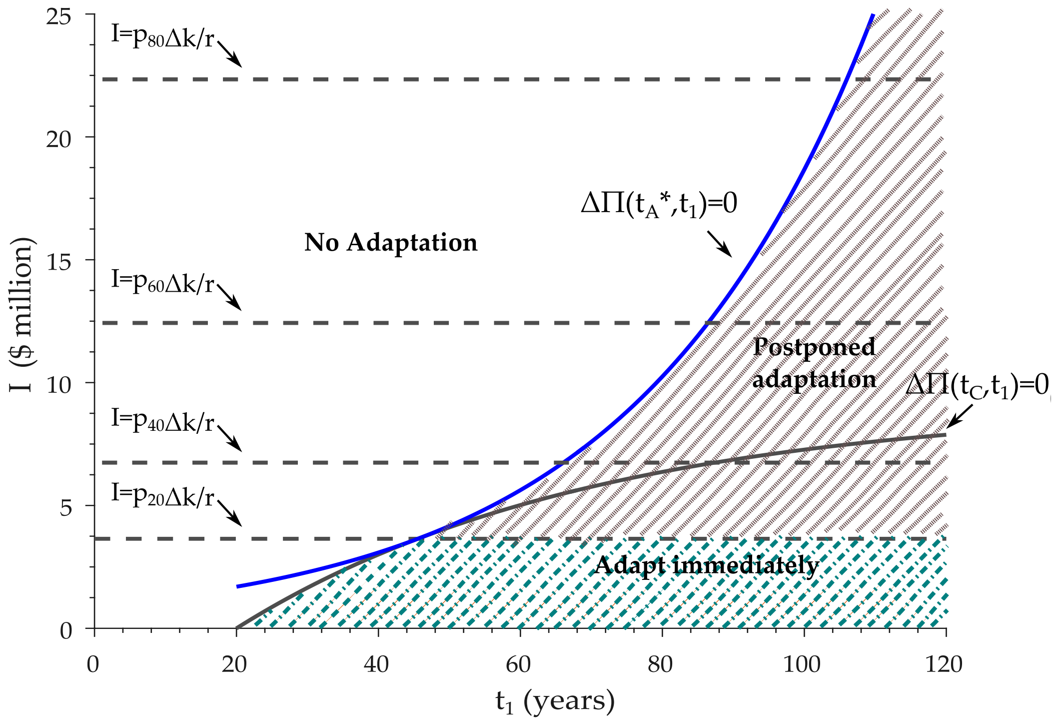


Figure 3: Adaptation by an informed operator- role of asset lifespan t_1 and cost of investment I
parameters
$k_0 = k_A = 1$, $k_C = 0.9$ [GWh/year], $p_0 = 0.1$ [\$ million/GWh], $t_C = 20$, $g_P = 0.03$, $r = 0.05$.

Whether informed operators decide to (i) adapt immediately at $t_A^* = t_C$, (ii) postpone adaptation with $t_C < t_A^* < t_1$ or (iii) decide to refrain from adaptation altogether, will depend on plant lifespan and cost of investment, among other things. Figure (3) illustrates these three adaptation regimes in $\{t_1, I\}$-space. First of all, adaptation at time of impact t_C is optimal when the annual benefits of adaptation at that time are equal to or exceed the cost of capital, that is, $p_{t_C}\Delta k \geq rI$, which requires a sufficiently small value of I, and when the remaining plant lifespan ensures an increase in the plant's net present value, i.e., $\Delta\Pi(t_C, t_1) \geq 0$, which in turn requires a sufficiently large value of t_1 and a sufficiently small value of I.

Second, if immediate adaptation is not optimal, it may be optimal to postpone. The operator will then wait till the annual benefits are equal to the cost of capital. Let us refer to the point in time when that happens as x, implicitly defined by the first-order condition $p_x\Delta k = rI$. In figure (3) we sketched a number of values for I associated with a wide range of values for x, e.g., $x = 40$ and $x = 60$. Of course, for adaptation to be optimal at time $t_A^* = x > t_C$, the change in the net present value must once again be non-negative, that is, $\Delta\Pi(t_A^*, t_1) \geq 0$,which requires a sufficiently large lifespan t_1. Third, note that for every t_1, there is an investment threshold such that adaptation will never be optimal for any I beyond that threshold. This explains the third and last regime. In sum, figure (3) shows that (postponed) adaptation is optimal for assets with long lifespans, so that there is sufficient time to recoup investment costs, and for assets with low investment costs, so that the net benefits of adaptation are more likely to be positive.

If the solutions of the ignorant and informed operator overlap then their realized profits will be identical and climate change information is said to be irrelevant.

Proposition 2. No-Regret Benefits and Costs and the (Ir)relevance of Climate Change Information.
Consider expected profits of a fully informed (Π^*) and an ignorant ($\widehat{\Pi}$) operator.
(i) *The case of no-regret benefits, $k_A > k_0$. The difference in profits between the informed and ignorant operator tends to be smaller the longer the remaining asset lifespan, the smaller the cost of retrofitting and the smaller the rate of interest.*
(ii) *The case of no-regret costs, $k_A \leq k_0$. The difference in profits between the informed and ignorant operator tends to be smaller the shorter the remaining asset lifespan, the larger the cost of retrofitting and the larger the rate of interest.*
Proof. Appendix B.2.

Since resources are always limited, climate change information should be leveraged and utilized in situations where it can tip an investment threshold and thus increase profits. Proposition 2 tells us that the conditions under which such critical situations occur, depend on whether the investment opportunity is characterized by either no-regret benefits or costs.

First, consider the case of no-regret costs. Since climate change damages now constitute the only rationale for investment the ignorant operator will never adapt, not even when climate change occurs at $t = t_C$, as he is assumed to be truly ignorant. The informed operator, however, will decide to adapt as soon as investment characteristics are sufficiently favorable, e.g., if the interest rate is small enough. Thus, once investment conditions are such so that adaptation becomes profitable for the informed operator, he will outperform the ignorant operator and climate change information has become relevant.

Second, consider the case of no-regret benefits. Both the ignorant and informed operator adapt once investment characteristics are sufficiently favorable, e.g., if the interest rate is small enough. When that happens both operators obtain the same level of profits and climate change information becomes de-facto irrelevant. In this case, climate change information becomes relevant only in those situations where the anticipated no-regret benefits were not very substantial to begin with, that is, where investment characteristics are actually not so favorable.

The core lesson here is that when adaptation is either very profitable or unprofitable due to substantial no-regret benefits and no-regret costs respectively, there is no need to engage in forecasting as the information obtained is unlikely to alter the status quo decision.

2.2.2. A stochastic model

Energy prices fluctuate due to changes in demand and supply. These changes, rooted in various socio-economic factors, including population growth, technological change and behavioral change, might be hard to predict for agents in electricity markets. Let us therefore consider a stochastic investment model in which investors face uncertainty over future electricity prices. In contrast to the first model, time is discrete and lasts only for two periods, $t = 1, 2$. Price uncertainty is introduced as follows; whereas price p_t is taken as given in period 1, $p_1 = p$, it jumps to $p_2 = \theta_p^H p$ with probability q and to $p_2 = \theta_p^L p$ with probability $1 - q$ in period 2, with $\theta_p^H > \theta_p^L$.

Climate change reduces plant capacity in period 2, from k_0 to $k_C = \theta_C k_0$ with $\theta_C < 1$. To adapt to climate change the operator can install additional cooling capacity which raises plant capacity to $k_A > k_C$. Let $a_1 \in \{0, 1\}$ and $a_2 \in \{a_1, 1\}$ denote the adaptation decision in period 1 and 2 respectively, where the restriction on the choice set of a_2 follows from the fact that adaptation is irreversible, and let us refer to $\pi_1(a_1)$ and $\pi_2(a_1, a_2; \theta_p)$ as the per-period profits in period 1 and 2 respectively. Once the second period arrives, the operator will maximize operating profits for a given a_1 and given realization of θ_p. In expectation second period profits then read:

$$E\left[\max_{a_2 \in \{a_1,1\}} \pi_2(a_1, a_2; \theta_p)\right] = \left\{ \begin{array}{ll} q \max\left(\theta_p^H p \theta_C k_0, \theta_p^H p k_A - I\right) + (1-q) \max\left(\theta_p^L p \theta_C k_0, \theta_p^L p k_A - I\right) & , \quad a_1 = 0 \\ p^e k_A & , \quad a_1 = 1 \end{array} \right\} \tag{14}$$

where $p^e \equiv q\theta_p^H p + (1-q)\,\theta_p^L p$ is the expected period 2 price. The value of the power plant at the beginning of period 1 is equal to the sum of (discounted) profits from period 1 and 2,

$$\Pi\left(a_1, a_2; \theta_p\right) = \pi_1(a_1) + \left(\frac{1}{1+r}\right) E\left[\max_{a_2 \in \{a_1,1\}} \pi_2(a_1, a_2; \theta_p)\right] \tag{15}$$

where

$$\pi_1(a_1) = \left\{ \begin{array}{ll} pk_0 & , \quad a_1 = 0 \\ pk_A & , \quad a_1 = 1 \end{array} \right\} \tag{16}$$

Taking into account how a_1 will influence first-period profits as well as the second-period adaptation decision for every state of the world θ_p, the operator maximizes the expected profits (15) by optimizing over a_1, that is, $\max_{a_1 \in \{0,1\}} \Pi\left(a_1, a_2; \theta_p\right)$. Depending on the parameter constellation, the manager will either find it profitable to invest immediately, invest never, or wait.[11]

Using this real options framework, we derive the impact of price uncertainty on the investment decisions of different type of plant operators, thereby assessing the relevance of climate change information. This time, we compare the adaptation decisions of a fully informed, an ignorant and somewhat

[11]Of course, it is well-known that in the presence of uncertainty and investment irreversibilities there is an option value to waiting, see Dixit and Pindyck (1994), Mensink and Requate (2005) and Traeger (2014).

ignorant operator. As before, an informed policy maker is fully aware of the impact of climate change, $\theta_C^* = \theta_C < 1$, whereas an ignorant manager, however, does not consider the impact of climate change at all, $\widehat{\theta}_C = 1$. We define a somewhat ignorant manager as one that does not consider the full impact of climate change, $\theta_C < \widetilde{\theta}_C < 1$.

We consider a mean-preserving increase of uncertainty. Let the variance of the second period price σ_p^2 be our measure of uncertainty and denote the second period price vector as $\underline{p}(x) = (p^H, p^L) = \left(\left(\theta_p^H + x\right) p, \left(\theta_p^L - \frac{q}{1-q} x\right) p\right)$. Then any increase in x, such that $p^H \geq 0 \cap p^L \geq 0$, leaves p^e unaltered but increases σ_p^2.

Proposition 3. Price Uncertainty and the (Ir)relevance of Climate Change Information.
Consider expected profits of a fully informed (Π^*), an ignorant ($\widehat{\Pi}$) and somewhat ignorant ($\widetilde{\Pi}$) operator.
(i) Locally, the difference in expected profits between the informed and ignorant operator is non-decreasing in the degree of price uncertainty, $\frac{\partial(\Pi^* - \widehat{\Pi})}{\partial x} \geq 0$. Globally, the greater the degree of uncertainty x the larger the range of investment costs for which $\Pi^* - \widehat{\Pi} > 0$.
(ii) Locally, the difference in expected profits between the informed and somewhat ignorant operator is ambiguous in the degree of price uncertainty, $\frac{\partial(\Pi^* - \widetilde{\Pi})}{\partial x} \gtreqless 0$. Globally, the greater the degree of uncertainty x the larger the range of investment costs for which $\Pi^* - \widetilde{\Pi} = 0$.
Proof. Appendix B.2.

The higher the degree of price uncertainty the more extreme future price realizations will be. This implies that the decision to adapt will increasingly depend on the price level. The reason is as follows. When high prices materialize, operators are eager to invest in cooling to boost production capacity, no matter how severe climate change is. When low prices materialize, operators are more likely to shy away from adaptation, even if climate change is severe. Anticipating this, operators will prefer to wait and then invest only if high prices materialize. Hence, there is an option value of waiting to invest.

Via this well-known option value mechanism, price uncertainty increases the expected return from waiting for both the somewhat ignorant and fully informed operator, making waiting their preferred strategy once the level of uncertainty is sufficiently high. When both type of operators prefer to wait, the difference in profits accruing to the two type of operators disappears completely. Proposition 3 tells us that via this global effect, price uncertainty tends to diminish the value of climate change information.

However, under conditions where only one of the operators prefers to wait, the operator who waits, gains relatively to the other type of operator. This is due to a standard speculation effect; conditional on waiting, more uncertainty only brings upside potential. In contrast to the beforementioned effect, this mechanism is only local. In sum, when price uncertainty grows it becomes increasingly less likely that providing the ignorant operator with climate change information will make her adapt today instead of postponing that decision.

While price uncertainty tends to induce the informed operator to postpone her adaptation decision (global effect), it leaves the expected profits of the ignorant operator unaltered, as she never adapts in the first place. In addition, in case the informed operator already decides to wait, the speculation effect further increases his payoff relative to the ignorant operator. Hence, only in this extreme case, where one compares the decisions of a fully informed and an ignorant operator, can price uncertainty unambiguously raise the relevance of climate change information.

The main insight emerging from our stochastic adaptation model is that when discrete decisions hinge on several types of information, lifting the veil of ignorance in merely one direction does little in promoting the optimal decision. The usefulness of forecasting to obtain and use climate change information is thus questionable in a context where uncertainty over future electricity prices, and thus uncertainty over the benefits of adaptation, persists.

3. A General Investment Model of Power Plant Adaptation

3.1. Model

In this section we present a more general, dynamic theory of power plant adaptation which encompasses the three analytically tractable models from the previous section. We consider power plant adaptation over a long but finite period of time, as in the first long-run benchmark model, and incorporate uncertainty over future electricity prices, as in the second long-run benchmark model. The theory presented here is also more general in that climate change manifests itself via climate scenarios. Instead of a single, negative climate shock, there is a continuous reduction in plant efficiency and capacity that unfolds slowly over a number of decades due to a trend of higher water temperatures and lower river flows. This approach allows us to apply the model empirically to two real-world power plants, making use of downscaled projections for river flow and temperature that are generated by a coupled hydrological-water temperature modeling framework forced with climate scenarios.

The operator faces a two stage investment problem. During stage 1 the operator decides on the usage of cooling water on a daily basis (short-run adaptation, see section 2.1), but she also has the option to retrofit the existing plant (long-run adaptation, see section 2.2) with a a supplementary cooling tower (or other appropriate cooling technology, as we explain in the next section). By providing additional cooling capacity, a cooling tower allows continuation of production on days when river flow levels are low and/or river water temperatures are high. It is assumed that the existing power plant will retire at time t_1.

At the beginning of stage 2 the owner decides whether he or she wants to invest in either a water efficient power plant C or opt for a less costly, water inefficient power plant O. If the owner chooses the latter, he or she obtains the option to retrofit this power plant at a later date, similar to the retrofit option held by the operator in Stage 1. As in Stage 1, the operator makes daily decisions with respect to cooling water intake during Stage 2. Stage 2 is assumed to end at time t_2, implying that the lifespan of the new plant equals $t_2 - t_1$.

3.1.1. Stage 1 - the present period

Let use define $\pi_O(p, T, L)$ and $\pi_C(p, T, L)$ as the instantaneous daily profits of a power plant with respectively a once-through (or "old") cooling system and a closed-cycle ("climate proof") system with e.g., a cooling tower, as a function of the variables price p, water temperature T and river flow L. Furthermore, let t_A, r and I_R represent respectively the time of adaptation, the rate of interest and the one-time capital cost of investment. Since p, T and L are all functions of the state variable time t, the present value $\Pi_1(t)$ of the existing power plant reads

$$\Pi_1(t) = \sum_{\tau=t}^{\tau=t_A} \left(\frac{1}{1+r}\right)^{\tau-t} \pi_O(\tau) + \sum_{\tau=t_A}^{\tau=t_1} \left(\frac{1}{1+r}\right)^{\tau-t} \pi_C(\tau) - \left(\frac{1}{1+r}\right)^{t_A-t} I_R \tag{17}$$

A power plant manager maximizes (17) by choosing the optimal date of adaptation t_A. In contrast to the first benchmark model, we solve this finite horizon problem with the aid of dynamic programming.

Additional notation is required in case of uncertainty. Suppose the electricity price follows a geometric Brownian motion, that is, $\{\ln(p(t)), t \geq 0\}$ follows a Brownian motion process with drift coefficient μ_p and variance parameter σ^2. Let

$$R_1(t_A, p) \equiv E_{t_A}\left[\sum_{\tau=t_A}^{\tau=t_1} \left(\frac{1}{1+r}\right)^{\tau-t_A} (\pi_C(p,\tau) - \pi_O(p,\tau))\right] \tag{18}$$

be the expected stream of additional revenues from retrofitting a plant with remaining lifespan $t_1 - t_A$. Then in each period the plant manager faces a choice between investing, and receiving $R_1(t_A, p) - I_R$, or waiting. One can then write the optimal value function $\Pi_1^*(t, p)$ as a sum of expected operating profits without adaptation, $W_1(t, p)$, and expected, additional operating profits from retrofitting, $V_1(t, p)$:

$$\Pi_1^*(t, p) = W_1(t, p) + V_1(t, p) \quad , \quad t \leq t_1 \tag{19}$$

where

$$W_1(t, p) = E_t \left[\sum_{\tau=t}^{\tau=t_1} \left(\frac{1}{1+r} \right)^{\tau-t} \pi_O(\tau, p) \right] \tag{20}$$

$$V_1(t, p) = \max \left\{ \left(\frac{1}{1+r} \right) E_t[V(t+1, p)], R_1(t, p) - I_R \right\} \quad , \quad p \in P \ \ , \ \ t = 1, 2, ..., t_1 \tag{21}$$

subject to the terminal condition, $V_1(t_1 + 1, p) = 0$ for $\forall p$. The finite horizon problem associated with the value function $V_1(t, p)$ can be solved using backward recursion. The solution a_t^* consists of a so-called exercise boundary; at any time t for any climate scenario $\theta_j = \left\{ T_t^j, L_t^j \right\}_{t=1}^{t=T}$, where index j refers to the specific IPCC scenario (status quo, RCP2.6, RCP8.5), there exists a price $p_A^*(t; \theta)$ such that for all $p_t \geq p_A^*(t; \theta)$ it is optimal to retrofit the power plant and wait otherwise.

3.1.2. Stage 2 - the future period

We use I_O and I_C to denote the cost of investment for a plant with a once-through (or ”old”) cooling system and a closed-cycle (”climate proof”) system with e.g., a cooling tower, respectively. Using similar notation as for stage 1, let us represent expected lifetime operating profits and additional benefits from retrofitting as $W_2^j(t, p) = E_t \left[\sum_{\tau=t}^{\tau=t_2} \left(\frac{1}{1+r} \right)^{\tau-t} \pi_j(\tau, p) \right]$ for $j \in \{O, C\}$ and $V_2(t, p) = \max \left\{ \left(\frac{1}{1+r} \right) E_t[V_2(t+1, p)], R_2(t, p) - I_R \right\}$ respectively, then the optimal period 2 value function reads

$$\Pi_2^*(t_1 + 1, p) = \max \left\{ W_2^C(t_1 + 1, p) - I_C, W_2^O(t_1 + 1, p) - I_O + V_2(t_1 + 1, p) \right\} \tag{22}$$

such that the lifetime present value of the plant can be written as the sum of period 1 and period 2 operating profits,

$$\Pi^*(t, p) = \Pi_1^*(t, p) + \left(\frac{1}{1+r} \right)^{t_1 - t} E_t \left[\Pi_2^*(t_1 + 1, p) \right] \quad , \quad t \leq t_1 \tag{23}$$

where $E_t \left[\Pi_2^*(t_1 + 1, p) \right]$ is the expectation at time t of lifetime operating profits of the plant to-be-build at time $t_1 + 1$.

3.2. Climate change information and the value of adaptation

As argued in Section 2, climate change information is relevant if it affects decision-making by the operator. One might wonder to what extent we can go beyond this qualitative statement to capture the usefulness of climate change information in one simple metric? In a recent study on climate change and timberland management, Guo and Costello (2013) argue that the value of (existing) technology in the context of climate change can be measured by the extent to which this technology is able to reduce damages from climate change. To measure this value of technology, or ”the value of adaptation” as they call it, Guo and Costello (2013) propose a novel methodology. In what follows, we apply their methodology to our power plant adaptation model and explain that their value of adaptation is essentially a measure of the (conditional) value of climate change information.

Inspired by Guo and Costello (2013), we use the present value function (23) to determine the value of adaptation. First, let us refer to the optimal day-to-day choices regarding water intake l^* and the optimal retrofitting decision a^* as adaptation on the intensive margin and extensive margin respectively.[12] Whereas the intensive margin involves marginal choices to deal with ambient conditions using existing capacity and technology (=short-run adaptation), the extensive margin entails a discrete choice to invest in new cooling capacity (=long-run adaptation). Second, with some abuse of notation we refer to $\Pi(t, \theta, l^*(\theta_l), a^*(\theta_a))$ as the optimal value of the power plant when the realized climate scenario is θ_j and the optimal decisions on the intensive and extensive margin are based on the anticipation of climate scenarios θ_l and θ_a respectively. Third, we can then decompose the net, negative impact of climate change $\Delta\Pi(t)$ as the sum of a direct, negative impact effect $\Delta\Pi_{CC}(t)$ and an indirect and positive information-induced adaptation effect $\Delta\Pi_{info}(t)$. Formally,

$$\Delta\Pi(t) = \Delta\Pi_{CC}(t) + \Delta\Pi_{info}(t) \tag{24}$$

where

$$\Delta\Pi_{CC}(t) = \Pi(t, \theta_c, l^*(\theta_w), a^*(\theta_w)) - \Pi(t, \theta_w, l^*(\theta_w), a^*(\theta_w)) \tag{25}$$

$$\Delta\Pi_{info}(t) = \Pi(t, \theta_c, l^*(\theta_c), a^*(\theta_c)) - \Pi(t, \theta_c, l^*(\theta_w), a^*(\theta_w)) \tag{26}$$

Note how the value of adaptation corresponds to the value of the power plant when the plant manager anticipates climate change ($\theta = \theta_l = \theta_a := \theta_c$) and acts accordingly minus the value of the power plant when the manager ignores (or does not anticipate) climate change ($\theta := \theta_c,\ \theta_l = \theta_a := \theta_w$). Hence, the value of adaptation is the value of having the "right" climate change scenario at your disposal and acting on it, conditional on available technology options.

Going one step further, one might be interested to know how much of the value of climate change information is due to changes along different decision margins. In principle, any decomposition that satisfies the identity $\Delta\Pi_{info}(t) = \Delta\Pi^{int}_{info}(t) + \Delta\Pi^{ext}_{info}(t)$ is feasible. The specific decomposition offered by Guo and Costello (2013) reads:

$$\Delta\Pi^{ext}_{info}(t) \equiv \Pi(t, \theta_c, l^*(\theta_c), a^*(\theta_c)) - \Pi(t, \theta_c, l^*(\theta_c), a^*(\theta_w)) \tag{27}$$

$$\Delta\Pi^{int}_{info}(t) \equiv \Pi(t, \theta_c, l^*(\theta_c), a^*(\theta_w)) - \Pi(t, \theta_c, l^*(\theta_w), a^*(\theta_w)) \tag{28}$$

This decomposition follows directly from eq. (26) by the addition and subtraction of an additional term, and collecting terms. As operators directly observe ambient temperature and river flow levels, their day-to-day decisions are not dependent on climate projections. The value of climate change information for the intensive margin $\Delta\Pi^{int}_{info}(t)$ is thus a 'theoretical' but nonetheless useful metric that allows one to assess the flexibility and value of current plant technology.

We empirically implement this 'accounting methodology' by assuming that ignorant and informed operators base their adaptation decisions on respectively the status quo and RCP2.6/RCP8.5 climate change scenarios.

3.3. Data and parameter values

3.3.1. Power plant characteristics and climate scenarios

We apply our model to two thermal power plants, the 1200 MW New Madrid coal-fired power plant in the USA and the 3122 MW Civaux nuclear power plant in France.[13] The New Madrid coal plant is

[12] Keep in mind that, by taking into account all input constraints, the multi-variable objective function, i.e., instantaneous profits, can be reduced to a single-variable objective function in either l or e (see section Appendix B.1.

[13] http://enipedia.tudelft.nl/wiki/New_Madrid_Powerplant; http://enipedia.tudelft.nl/wiki/Civaux_Powerplant

located at the Mississippi river and depends on a once-through (O-T) cooling system. The Civaux nuclear plant is located near a very small river. Consequently, the plant depends on cooling towers to dispose off its waste heat. These are connected to the plant by a closed-cycle (C-C) water circuit. The water vaporized in the cooling tower is drawn from the river.[14]

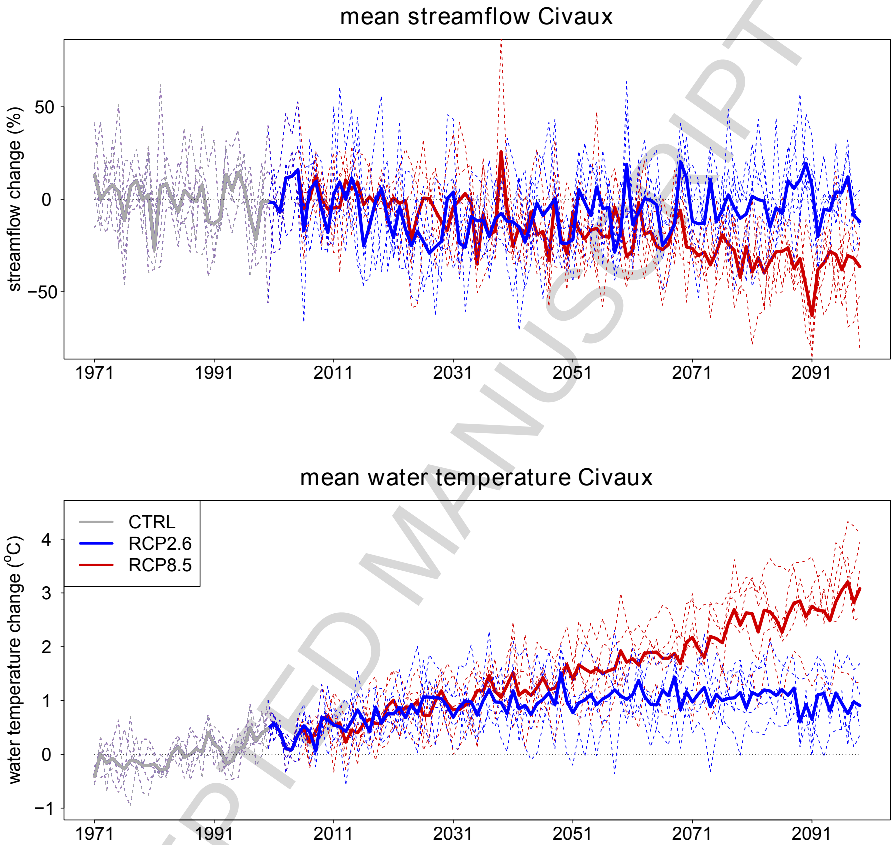


Figure 4: Projections of streamflow and water temperature for the Civaux nuclear plant (1971-2099).

We produced river flow (Q) and water temperature (T) projections under future climate for our selection of power plants. These projections with a daily timestep are produced by a coupled hydrological and water temperature modeling framework (van Vliet et al., 2012b). They were generated using climate model simulations for two representative concentration pathways (RCPs), that is, 2.6 (van Vuuren et al., 2011) and 8.5 (Riahi et al., 2011), as input. We constructed three scenarios for the period 2011-2080: no climate change (status quo), a (high) RCP8.5 and a (low) RCP2.6 scenario (Appendix C). In figure (4) we graph these simulations of mean annual streamflow and mean annual water temperature for the river that provides the Civaux nuclear plant with its cooling water. Clearly, there are trends in all simulations, except for Civaux's RCP2.6 streamflow where there seems to be a reversal occurring mid-century, indicating a deterioration in the environmental inputs to the power plant.[15]

3.3.2. Economic parameters

For electricity prices, interest rates, fuel costs and plant (retrofitting) investment costs, we make use of estimates from the literature, which are listed in Table (1). Fuel costs refer to average 2011 market

[14]The choice for these two plants is based on (i) the fact that they represent different technologies and different cooling systems and (ii) the knowledge that these plants, according to the projections presented by van Vliet et al. (2012b) , seem to be fairly average in terms of their vulnerability to climate change.

[15]Please note that plant production and profits are especially affected by summer extremes. Since that information is not presented in figure (4) it only represents a partial picture of the effects from climate change.

prices, which are either country-specific (nuclear) or state-specific (coal). The electricity price for the New Madrid power plant refers to the average 2011 MISO Illinois Hub wholesale price. For the Civaux plant we took the average 2011 French industry retail price net of taxes from IEA (2012), and deducted an additional 50%, which seems in line with day-ahead prices recorded at the European EPEX SPOT wholesale market over 2011.

We assume that both uranium and coal remain relatively abundant. The future real price of coal will also depend on the availability and price of gas and the price of CO_2 permits. In our baseline scenario we assume the costs of coal delivered to grow with an annual rate of 1.5%. For uranium, we base our estimate of the growth rate of the cost of uranium on a simple uranium resource elasticity model (see MIT (2011)) and adopt a conservative value of 0.5%. In our baseline scenario, we assume that for both power plants the price of electricity will grow at the same rate as the cost of fuel. Operators are assumed to discount future costs and benefits by a risk-adjusted interest rate. Based on IEA and NEA (2010) and Rohlfs and Madlener (2010), we pick $r = 0.05$ as our baseline estimate.

The cost-estimates for retrofitting thermal power plants with O-T cooling systems with cooling towers are primarily based on a report by EPRI (2011). We base our calculations of investment cost only on the cost of capital and abstract from other potential costs including revenues from extended outage time during construction, because of a lack of (reliable) estimates. The fleet of power plants considered in the retrofit study by EPRI (2011) consists of 39 nuclear facilities (joint capacity 60 GW) and 389 fossil-fueled plants (joint capacity 252 GW). The capital costs of retrofitting equal \$19.6 billion and \$42.4 billion for the fleet of nuclear power plants and fossil fuel power plants respectively. Using these estimates we find that the overnight cost of a retrofit equals \$ 326.67 million per GW capacity (nuclear) and \$ 168.25 million per GW capacity (coal). Note that our estimates abstract from considerations of economies of scale.

Since the Civaux plant is already equipped with cooling towers, we interpret its retrofit option as (i) an investment in a dry-cooling system, (or (ii) an investment in connecting the plant to an alternative heat sink, say a nearby city with a demand for district heating or cooling). We cap the maximum investment cost of this retrofit option at the cost level associated with retrofitting a O-T cooled nuclear power plant with cooling towers, as this is known to be an expensive retrofitting option. As retrofitting a plant with a dry-cooling system is likely to be even more costly, we view this as a lower bound of the retrofit cost.

For new power plants to be build in stage 2, we rely on common numbers for design lifespan, and set plant lifespan equal to 40 years (nuclear) and 50 years (coal). For the existing New Madrid coal plant, starting in 2011, we impose a remaining lifespan of 20 years, with production ending by December 31, 2030. This seems reasonably given the fact the two 600MW units of the plant have been in operation from 1972 and 1977 onwards. For the Civaux nuclear plant, which was taken into commercial operation in 2002, we take December 31, 2040 as the last production day.

The cost of investment of a new power plant refers to overnight costs of investment. Analyzing recent investor's plans for building new generators, Shuster and Klara (2010) finds that a total investment of \$141.5 billion is required for a 96 GW capacity upgrade of the US fleet of coal plants. An estimate based on his numbers, \$1.48 billion per GW, is fairly low compared to a more recent estimate by IEA and NEA (2010), which puts coal power at \$2.108-2.433 billion per GW capacity. We take a middle ground and pick \$2.1 as our baseline estimate. These estimates presumably refer to new plants with a C-C cooling system, as this technology has become the industry standard in recent years. To obtain a cost estimate for coal plants with an O-T system, we assume that O-T and C-C cooling systems account for respectively 4% and 10% of total capital costs.

For nuclear power the estimate by EIA and DOE (2010) for France is \$3.86 billion per GW. A study by Joskow and Parsons (2009) based on recent plant constructions in Japan and Korea, as well as plans for new plants in the US, puts the cost of nuclear power at $4 billion per GW. A relatively recent study by MIT (2009) confirms that investment costs (and capital costs) for both coal and nuclear have increased, but relatively more so for nuclear. The cost estimate for a nuclear power plant with a dry-cooling system is obtained from (Zammit, 2012), who argues that dry-cooling typically adds an additional 10% to the capital cost of a C-C cooled power plant. To ensure that the additional costs of equipping a new plant with dry-cooling do not exceed the costs of retrofitting a plant with that same technology, we cap the total additional cost of dry-cooling at $\frac{2}{3.122} * 10 = 6.4\%$ of plant cost.

Parameter values for the various environmental restrictions, i.e., T_{max}, ΔT_{max} and γ, are taken from van Vliet et al. (2012b).

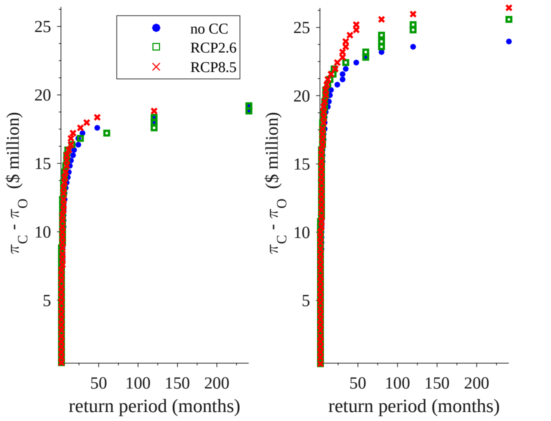
Parameter description	Coal power	Nuclear power	Source
Net (gross) fuel cost ($ cents per KWh)	1.42 (0.65)	0.93 (0.33)	EIA (2014), IEA and NEA (2010)
Wholesale electricity price ($ cents per KWh)	3.86	6.97	EIA (2012), IEA (2012)
Retrofit cost ($ million per GW capacity)	168.25	326.67	EPRI (2011)
Investment cost new plant with O-T cooling ($ million per GW capacity)	1974	-	Shuster and Klara (2010), IEA and NEA (2010)
Investment cost new plant with C-C cooling ($ million per GW capacity)	2100	3860	Shuster and Klara (2010), IEA and NEA (2010)
Investment cost new plant with dry-cooling ($ million per GW capacity)	-	4246	Shuster and Klara (2010), IEA and NEA (2010) Zammit (2012)

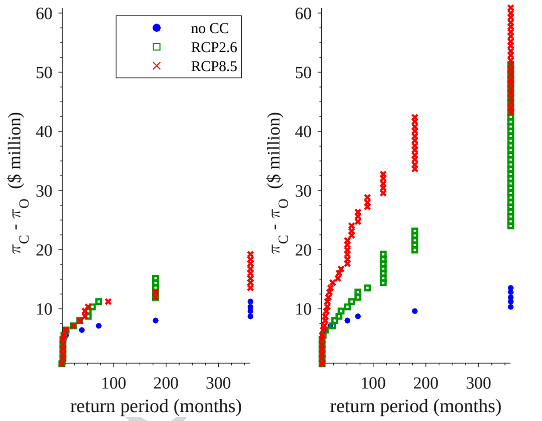
Table 1: Key characteristics of New Madrid and Civaux thermal power plants.

4. Results

4.1. Main results with deterministic prices

We first analyze power plant adaptation in a fully deterministic setting, abstracting from price uncertainty. Figure (5) plots lost profits $\pi_C - \pi_O$, that is, the monthly costs from not having installed the more advanced cooling technology, against return time. In each of the two sub-figures, the left and right panel represent respectively the present and future period. Under the RCP8.5 scenario and (to a somewhat smaller degree) the RCP2.6 scenario the level of lost profits increase over time. This occurs because climate change amplifies the load reduction and efficiency reduction effects. During particularly dry and hot months a plant that is retrofitted with a cooling tower or dry-cooling technology therefore has superior performance, which according to our numerical analysis translates into additional revenues that can be as high as $25 and $60 million per month in nominal terms for the coal and nuclear plant respectively. If one takes into account that the coal plant features only $\frac{1}{3}$ of the generating

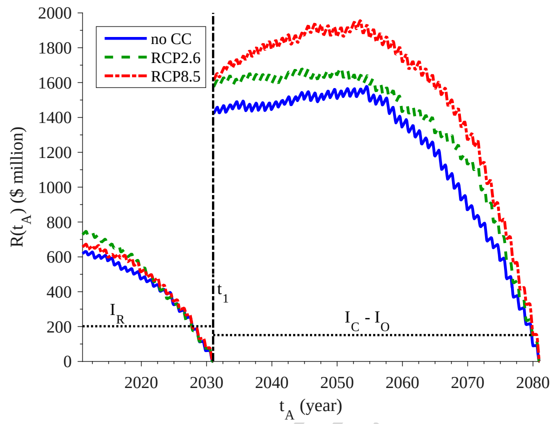


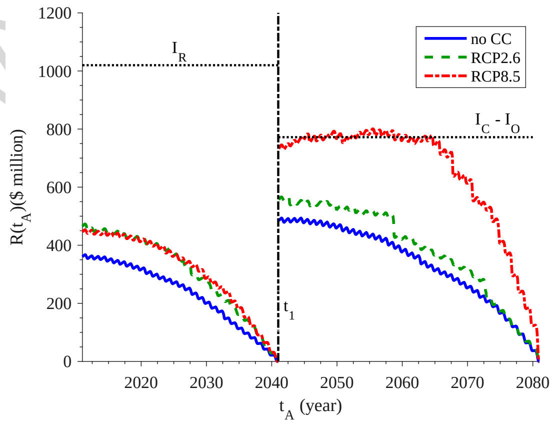


(a) Coal plant (O-T cooling): 2011-30 and 2031-80. ($g_p = g_c = 0.015$)

(b) Nuclear plant (C-C cooling): 2011-40 and 2041-80. ($g_p = g_c = 0.005$)

Figure 5: Lost power plant profits from adverse ambient conditions.





(a) Coal plant (O-T cooling): 2011-30 and 2031-80. ($g_p = g_c = 0.015$)

(b) Nuclear plant (C-C cooling): 2011-40 and 2041-80. ($g_p = g_c = 0.005$)

Figure 6: Trajectory of gross benefits from having the more advanced cooling technology.

capacity of the nuclear plant, the gains from retrofitting the New Madrid coal plant with its vulnerable O-T cooling system appear relatively large.

As explained in section 3.1, a forward-looking and fully informed operator faces a trade-off between the reward $R(t_A)$, that is, the discounted gross benefits (or avoided losses) from having the more advanced cooling technology, and the (additional) one-time cost of investment needed to obtain it. As one can see in figure (6), the premium that is paid for acquiring this technology is larger under a retrofit (I_R) than when it is part of a new-to-be-build plant ($I_C - I_O$).

In figure (6) we plot the reward as a function of the investment date t_A. The profile of $R(t_A)$ is shaped by two counteracting forces. With electricity prices, fuel costs and load reductions continuously growing over time, the reward $R(t_A)$ can actually increase if investment is postponed. This occurs because with discounting the reward function implicitly attaches a relatively large weight to short-term revenues (see eq. (18)). Because postponement also means that the operator has a shorter remaining time horizon to recoup investment, however, we find in all but one case (right panel Figure (6a) that the benefits from adaptation decline monotonically over time. This implies that *if* an operator wants to acquire the more advanced cooling technology, she will do so immediately.

Adopting an annual growth rate for the price of electricity g_p that ranges between 0-3%, our numerical analysis then puts the net losses from climate change at $25-87 million (coal) and $121-159 million (nuclear), where the lower and upperbound refer to the RCP2.6 (with g_p=0) and the RCP8.5 scenario (with $g_p = 0.03$) respectively. In our baseline setting, where prices and costs grow at the same rate, and assuming a conservative estimate of the share of fuel costs in total operating costs, which we put at 75% for the coal plant and at 25% for the nuclear plant respectively, net losses from climate change are found to be relatively modest, but certainly not negligible at 1.0% and 0.9% of net operating profits under the RCP8.5 scenario. These loss shares would likely be substantially higher when expressed in terms of net profits.

Coal plant			**Nuclear plant**		
$\{g_p, g_c\} = \{0, 0.015\}$	2011-30	2031-80	$\{g_p, g_c\} = \{0, 0.005\}$	2011-40	2041-80
$\Delta\Pi_{info}^{int}$	81.8 (79.7)	41.6 (49.1)	$\Delta\Pi_{info}^{int}$	127.6 (128.4)	14.0 (20.6)
$\Delta\Pi_{info}^{ext}$	0.8 (0.7)	0 (0)	$\Delta\Pi_{info}^{ext}$	0 (0)	0 (0)
$\Delta\Pi_{info}$	82.6 (80.4)	41.6 (49.1)	$\Delta\Pi_{info}$	127.6 (128.4)	14.0 (20.6)
$\{g_p, g_c\} = \{0.03, 0.015\}$			$\{g_p, g_c\} = \{0.03, 0.005\}$		
$\Delta\Pi_{info}^{int}$	125.8 (123.1)	275.4 (406.4)	$\Delta\Pi_{info}^{int}$	201.6 (207.5)	7.7 (9.3)
$\Delta\Pi_{info}^{ext}$	0.8 (0.7)	0 (0)	$\Delta\Pi_{info}^{ext}$	0 (0)	0 (0)
$\Delta\Pi_{info}$	126.6 (123.8)	275.4 (406.4)	$\Delta\Pi_{info}$	201.6 (207.5)	7.7 (9.3)

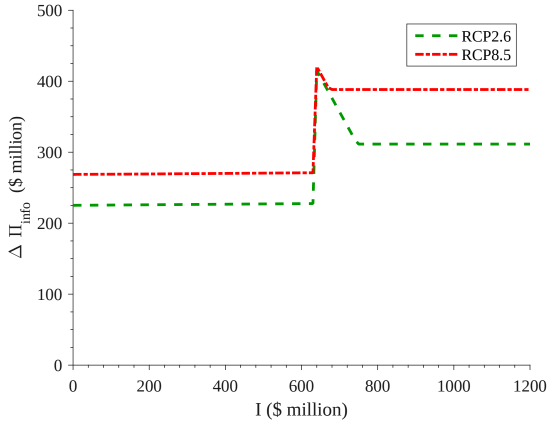
Table 2: Value of climate change information by intensive and extensive margin ($ million)

For each power plant and adaptation margin, Table (2) lists the value of climate change information $\Delta\Pi_{info}$ under two different price and cost scenarios and presents them separately for each time period. The numbers without and within brackets refer to the RCP2.6 and RCP8.5 climate scenarios respectively. For both the coal and nuclear plant the total value of $\Delta\Pi_{info}$ is found to be sizable, with present values that range between $124-530 and $142-217 million respectively. In terms of net operating profits, and again assuming $g_p = 0.015$ and $g_p = 0.005$ for coal and nuclear respectively, the value of climate change information amounts to approximately 6.0% and 1.0% of net operating profits. This value originates almost completely from adaptation along the intensive margin though: the day-to-day choices of key inputs (fuel and cooling water) go a long way in dealing with weather fluctuations.

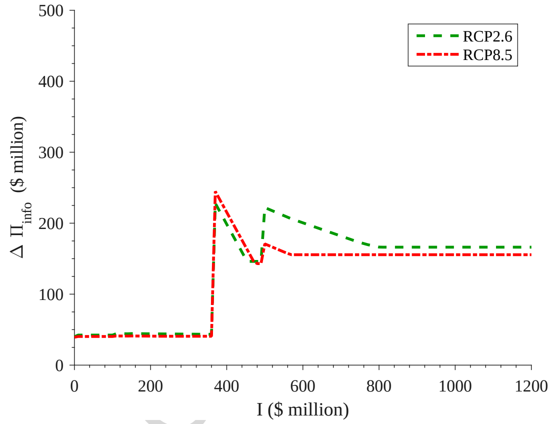
Interestingly, our previous finding also implies that the value of climate change information for the extensive margin, $\Delta\Pi_{info}^{ext}$, is negligible. This is because adaptation of the New Madrid coal plant through retrofitting is already profitable today, even under the assumption that current climatic conditions will last, entailing substantial no-regret benefits (see Proposition 2). As shown in the left "panel" of figure (6a), the gross benefit from retrofitting attains its highest level at $t_A = 0$ and exceeds the cost of retrofitting, which amounts to just a little bit over $200 million, see Table (1), under all climate scenarios. The net benefits of C-C cooling are even more sizeable for the future plant (see right panel figure (6a)).

Conversely, adaptation by means of retrofitting is never cost efficient for the Civaux nuclear plant, even under the assumption that the most extreme climate scenario (RCP8.5) will materialize. Here the costs of retrofitting, close to $1 billion, clearly exceeds gross benefits, which barely sum up to $0.45 billion (left "panel" figure (6b)). For the new-to-be-build plant in 2041 we find that the net benefits of dry cooling are still negative, although the gap between costs and benefits has become much smaller (right "panel" figure (6b)).

As expressed formally in Proposition 2, our case studies thus indicate that climate change information does not necessarily alter investment decisions. Whether the decisions of informed and uninformed operators overlap, depends on both (i) the magnitude of the anticipated climate impacts under the different scenarios and (ii) various economic parameters. To illustrate this point, figure (7) plots the value of climate change information (see Section 3.2) for each power plant as a function of the cost of



(a) Coal plant (O-T cooling).



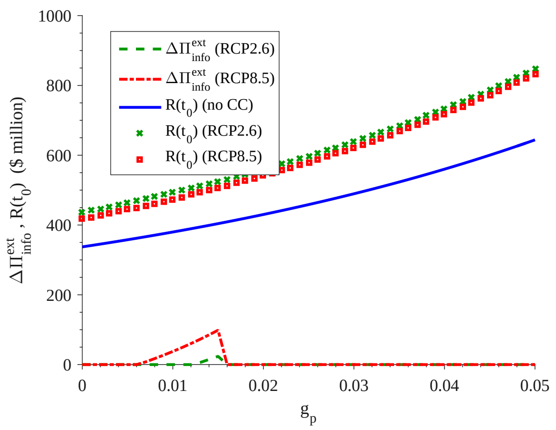
(b) Nuclear plant (C-C cooling).

Figure 7: Value of climate change information as a function of investment cost.

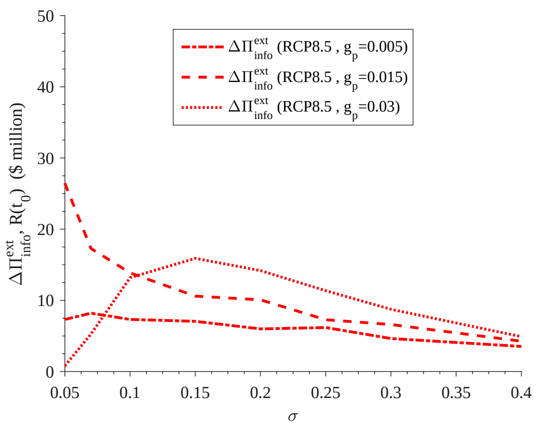
retrofitting. Going from left to right, the total value of adaptation peaks when the cost of retrofitting attains intermediate values. This can be explained as follows. When the cost of investment is relatively small, even an ignorant operator will choose to adapt to capture no-regret benefits from the current climate. Under these conditions climate change information is not very relevant.

Going further to the right, an ignorant operator mistakenly chooses to forgo the retrofit option. As a result, net climate damages will be lower for the informed operator. Hence, climate change information is most relevant and valuable for intermediate investment costs. When the cost of investment is relatively high, both the ignorant and informed operator will choose not to retrofit the existing plant, and the value of adaptation falls again.[16] Operators also adapt to fluctuations in ambient conditions by changing the inputs of fuel and cooling water. By doing so she dampens the direct impact of climate change. The value of adaptation therefore remains positive for low and high investment costs.

4.2. Power plant adaptation under price uncertainty



(a) The impact of the electricity price growth rate g_p.



(b) The impact of price uncertainty σ.

Figure 8: The value of climate change information.

To analyze the impact of uncertainty, we assume that the price of electricity follows a stochastic process. Here we focus on the nuclear power plant. To facilitate the interpretation of our results, we

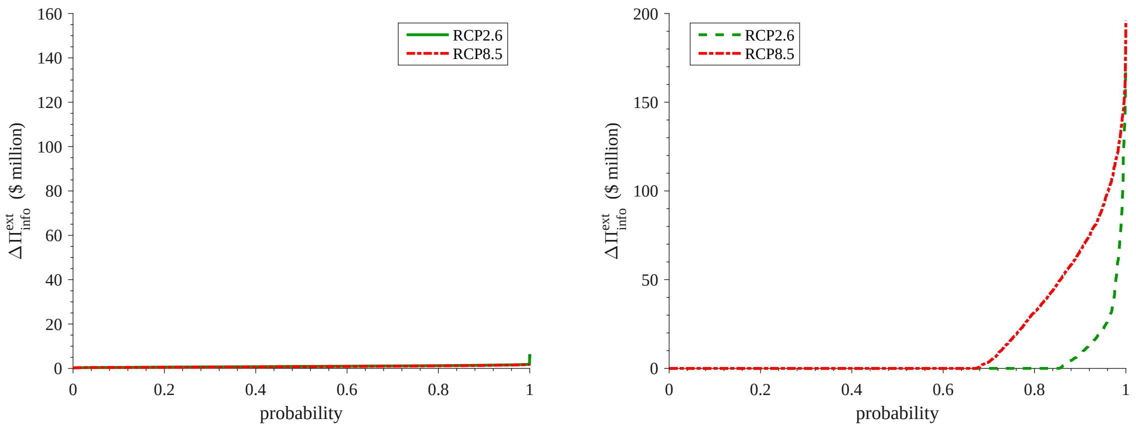
[16]The value of climate change information peaks twice for the nuclear power plant (see 7b) The second peak occurs when the informed operator decides to retrofit the new plant that was built in 2041 while the ignorant operator does not.

first analyze the relationship between the growth rate of the electricity price, g_p, on the one hand, and the gross benefits of retrofitting and the value of climate change information on the other hand. Figure (8a) shows that a rapidly growing electricity price will magnify the gross benefits from retrofitting, as the avoided revenue losses from production interruptions will increase.

More noteworthy in figure (8a) is the value-of-adaptation curve, which is characterized by a 'bump'. This bump represents the gain for a fully informed operator that correctly decides to equip the new plant to be built in 2041 with a dry cooling system while an ignorant operator incorrectly decides to withhold this investment. In present value terms these future benefits from taking climate change into account are relatively modest though. Going further to the right, the no-regret benefits from dry cooling become apparent even for the ignorant operator, and the additional benefits that accrue to a fully informed operator disappear.

Finally, sub-figure (8b) plots the value of climate change information in the RCP8.5 scenario as a function of price uncertainty. Two observations can be made. Locally, the impact of price uncertainty is ambiguous due to a speculation effect; conditional on waiting, more uncertainty brings more upside potential and raises expected profits. This effect can either increase or decrease the value of climate change information (see Proposition 3). Globally, however, there is a clear negative relationship between σ and $\Delta\Pi^{ext}_{info}(t_0)$, showing that climate change information becomes increasingly irrelevant if price uncertainty increases. These findings mirror our formal results from Proposition 3. When price uncertainty increases, fine grained climate impact information is less likely to influence the decision to adapt, the choices of an ignorant and fully informed operator will become increasingly similar and the value of climate change information diminishes.

4.3. Robustness - parameter sensitivity



(a) Coal plant (O-T cooling).

(b) Nuclear plant (C-C cooling).

Figure 9: Monte Carlo analysis.

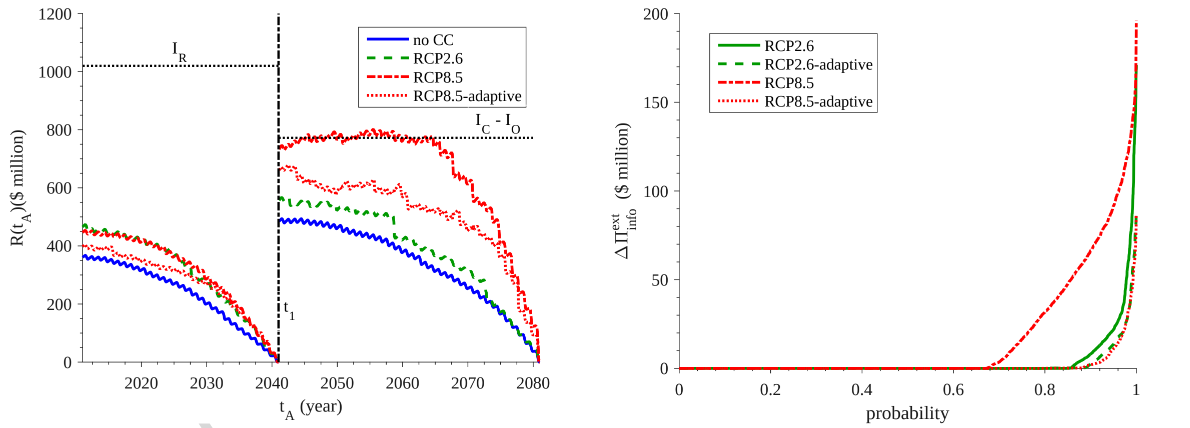
Our analysis of two different power plants thus far suggests that although plant operators benefit substantially from a thorough knowledge of current climatic conditions, their adaptation decisions are hardly affected when they use correct projections of future climatic conditions. In that sense, operators don't gain much from making or acquiring such projections. One might worry that this conclusion results from an inaccurate or deliberate selection of parameter values. To check the robustness of our result, we performed an additional numerical experiment in the form of a Monte Carlo analysis.

The set-up of our Monte Carlo experiment is as follows. As before, we simulate power plant decisions by both ignorant and fully informed operators for all three climate scenarios. For each power plant we run a total of 5000 simulations. For each separate simulation, we randomly draw a set of key parameters from uniform distributions, that is, $g_c \in [0, 0.03]$, $g_p \in [0, 0.03]$, $r \in [0.03, 0.05]$ and $I_R \in \left[\frac{\overline{I_R}}{2}, 2\overline{I_R}\right]$, where $\overline{I_R}$ is the relevant plant retrofit cost constructed using information on plant capacity and the estimates in Table (1). All other parameter values are similar to those used for the previous simulations.

The results of our Monte Carlo analysis are displayed in figure (9a). Here we used the data from our numerical experiment to draw an inverse cumulative distribution function of $\Delta\Pi^{ext}_{info}(t_0)$, that is, the value of climate change information along the extensive margin at t_0. Clearly, $\Delta\Pi^{ext}_{info}(t_0)$ is negligible for the coal plant across the entire simulation space. This confirms our previous interpretation: retrofitting this plant comes with major no-regret benefits such that for a large range of parameter values it would make sense to adapt today. Hence, to maximize net present value of this O-T cooled plant the operator only needs to know current climatic conditions.

For the nuclear plant we find that $\Delta\Pi^{ext}_{info}(t_0) = 0$ in respectively 70% and 87% of all simulations for the RCP8.5 and RCP2.6 scenario. For the RCP2.6 scenario the distribution of the remaining 13% is very uneven, with $\Delta\Pi^{ext}_{info}(t_0) >$ \$50 million in less than 2% of all simulations. This figure contrasts sharply with the RCP8.5 scenario where $\Delta\Pi^{ext}_{info}(t_0)$ exceeds \$50 million in about 15% of all cases. More in general, information on future climatic conditions is clearly more valuable under the RCP8.5 scenario. Figure (9b) shows that the total area under the inverse cumulate distribution function is much larger for the RCP8.5 than the RCP2.6 scenario.

4.4. Robustness - adaptive vs. ignorant operator



(a) Nuclear plant (C-C cooling). 2011-40 and 2041-80. ($g_p = g_c = 0.005$)

(b) Value of climate change information for nuclear plant (C-C cooling)

Figure 10: Sensitivity analysis nuclear plant

To assess the net benefits of predicting future river flow and water temperature levels, we have contrasted the decisions of an informed and ignorant operator. While the former correctly anticipates the relevant RCP scenario, the latter assumes that conditions under the control period 1971-2000 last till the end of the 21th century. One may object, however, to our choice of taking the ignorant operator as the benchmark against which we compare the decisions of the fully informed operator. Decades from now, in 2031 or 2041, when he has to decide on the yet to be built power plant, the ignorant operator still bases his decisions on the 1971-2000 climate. It seems likely that operators will want to incorporate recent climate information in their projections to deal with the uncertainty of climate change.

To analyze the robustness of our results, we introduce the concept of an 'adaptive' operator, who bases his decisions on climatic conditions of the recent past. To be precise, at any time t the adaptive operator assumes that the climate of the last 10 years will last till the end of the time horizon. For example, at the beginning of 2041 the operator will assume that the river flow and temperature levels observed over the period 2031-2040 will be ’repeated’ four times, with the period 2071-2080 constituting the last cycle. As time proceeds and the operator makes new ’observations’, he updates his information and his projections change. In figure (4) we observe that water temperature and, to a somewhat smaller degree, river flow relevant to the Civaux nuclear plant follow a clear trend. This implies that the projections of the adaptive operator will be characterized by clear trend too. Hence, in contrast to the ignorant operator, the adaptive operator does not, per se, become progressively more (or less) wrong about climate change.

In figure (10a) we display the dynamic trajectory of the benefits associated with upgrading to dry-cooling for the Civaux nuclear plant. As in figure (6b), we show them for the original three scenarios, but here we also add the trajectory of benefits for the RCP8.5 scenario under the assumption of an adaptive operator. For example, $R(2061)$ for the adaptive operator is the projected gross reward from upgrading to dry-cooling in 2061, which is based on the assumption that the climate from 2051-2060 will repeat itself over the next two decades between 2061-2080 before the plant is taken out of production.

Clearly, the benefits of dry-cooling that are expected by the adaptive operator tend to be larger than those of the ignorant operator, but smaller than those of the informed operator. This outcome seems intuitive; in a world with progressive climate change the benefits from adaptation tend to grow over time, and the projections of an operator who uses recent climate information will be closer to the informed operator than the projections of an operator who uses outdated information. Of course, the fact there is a clear trend in the evolution of climatic conditions is key, otherwise there is no guarantee that information from the recent past does better per se compared to information of the more distant past.

Next, we repeat our Monte Carlo analysis. This time we contrast the informed operator with both the ignorant and adaptive operator. Figure (10b) displays the results of this numerical experiment. When the adaptive operator is taken as the benchmark, it is found that the value of climate change information, that is, the added benefits from correctly anticipating future river flow and water temperature levels, is much smaller than when compared with the ignorant operator. The improvement of the adaptive operator over the ignorant operator is particularly large under the RCP8.5 scenario. Only in about 12% of the cases does the informed operator perform better than the adaptive operator, that is, $\Delta\Pi^{ext}_{info}(t_0) > 0$. We also find that $\Delta\Pi^{ext}_{info}(t_0)$ does not exceed \$100 million in any of the 5000 simulations. Hence, our exercise strengthens our initial result that was based on using the ignorant operator as a benchmark; in a fairly small number of cases will information on climate change alter adaptation decisions and improve a plant’s net present value.

5. Conclusion

As heat waves and droughts translate into fewer revenues for thermal electricity producers, there appears to be a strong rationale for these producers to invest in climate adaptation. Our findings for two different power plants show that operators that base their decisions on current climatic conditions are likely to make identical choices and perform similar in terms of expected plant profits as operators that are fully ’informed’ about future climatic conditions. The latter implies that projections of future river flow and temperature levels under climate change do not necessarily create additional value for those power plant operators and investors that are already well-informed about current climatic conditions.

As illustrated by our theory and demonstrated by our empirical application, there are two main reasons why climate change information is unlikely to overturn an adaptation decision. First, although climate change scenarios indicate a substantial deterioration of ambient conditions, the literature has failed to acknowledge, somewhat ironically, that power plants essentially embody a flexible type of technology, which partly shields operators from these effects. The additional incurred damages under scenarios with climate change compared to scenarios without climate change are thus relatively small. For the coal power plant using O-T cooling, it would already be profitable to adapt today by constructing a cooling tower, while the nuclear power plant with tower cooling has already been adapted, and experiences limited benefits from further adaptation (e.g., a retrofit to a dry cooling system).

Considering adaptation by means of retrofitting, one would thus expect, all things equal, that only a limited selection of power plants would retrofit the existing plant once new information on climate change is received. In particular, this category of plants might contain those plants using O-T cooling with limited constraints on production under current climate, but strong adverse impacts under future climate. Somewhat similarly, when an investor decides whether to equip a new to be built power plant with a water-saving C-C system, he is likely to do so even with the knowledge of current climate conditions. This occurs because according to our data the difference in investment costs between a plant with a O-T system and C-C system are currently relatively small.

Second, price uncertainty imposes additional economic barriers to adaptation. This argument proceeds in two steps. To begin with, price uncertainty entails that extreme outcomes, where future prices are either relatively low or relatively high compared to today's prices, become more likely. Postponing adaptation is then the preferred option. This impact of price uncertainty on decision making is, of course, well-known. On top of that, however, as adaptation is more likely to become either very profitable or very unprofitable, it becomes less plausible that climate change information will overturn the operator's decision. Hence, price uncertainty decreases the value of climate change information.

Adaptation by means of retrofitting existing infrastructure assets may thus not necessarily constitute an efficient strategy to cope with the risks of climate change. In the electricity sector, newly-built power plants with C-T cooling, dry cooling or other 'climate-proof' cooling technology may gradually replace older power plants that rely on O-T cooling systems. In the interim, a temporary higher exposure to the risks of climate change induced electricity supply interruptions cannot be ruled out. Whether this long-term adaptation strategy is socially optimal or not depends on whether any existing market failures are exacerbated by potential retrofitting decisions. For example, if electricity supply is subject to market power, operators might deliberately underinvest in cooling capacity to increase profits.

Our study may also be seen as a test case for climate adaptation in other network sectors, such as roads, railway, water and ICT. In these sectors the degree of government control over investment, development and retirement of infrastructure assets is limited. While public or semi-public energy utilities are hardening their assets (e.g., Russell (2013)), it remains to be seen whether current market and regulatory conditions will bring about a timely and adequate response by private owners. Our analysis illustrates that even for such relatively long-lived and relatively vulnerable assets as thermal power plants, climate change impacts may not be sufficiently strong so as to tip the private investment threshold.

Our work also raises questions regarding the scope of adaptation as an instrument to confront the challenges of climate change. As investment in adaptation might be (i) (privately) inefficient in some sectors (e.g., electricity markets) or (ii) simply technologically infeasible in other 'sectors' (e.g., natural ecosystems), a focus on mitigation remains crucial in reducing expected climate change damages. Interestingly, there are various ways in which mitigation itself may feed back into society's incentives to pursue adaptation in the power sector. While mitigation is likely to decrease the share of coal in the power mix, thereby reducing the power sector's dependence on water, it may also increase the sector's reliance on water if it increases nuclear energy and if coal plants with carbon capture and storage (which both have lower overall efficiency) come to fruition on a large scale (see Byers et al. (2016)). Furthermore, the transition towards a world with a considerable supply of renewable energy may affect electricity prices for a long time to come, which in turn will influence the incentives for existing power plant operators to adapt.

Acknowledgements

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Author Contributions

CWJB designed the study, contributed to power plant modeling, performed the theoretical and numerical analysis and contributed to the manuscript. GPJD contributed to power plant modeling and contributed to the manuscript. MTHvV simulated the impacts of climate change on river flow and water temperature and contributed to the manuscript.

Appendix A. Table Overview of Parameters and Variables

a_t	adaptation decision at time t
α	share of waste heat not discharged by cooling water
c	gross marginal energy cost of production [$/GWh]
C_p	heat capacity of water [MJ/ kg K]
δ	temperature sensitivity of plant efficiency
$e\,(\bar{e})$	fuel energy intake (upperbound) [MJ/s]
ϵ	share of waste heat released into air
$\eta\,(\eta_D)$	plant efficiency (at $T = T_D$)
EZ	densification factor
g_c	growth rate energy fuel costs
g_p	growth rate electricity price
γ	maximum permissible fraction of river flow for cooling
$\bar{h}$	maximum heating of coolant [K]
I	investment cost of adaptation [$]
I_C	investment cost new plant, open cooling [$]
I_O	investment cost new plant, closed (or dry) cooling [$]
I_R	investment cost, open (or dry) cooling retrofit [$]
k	plant capacity [MW]
k_0	initial plant capacity [MW]
k_C	plant capacity after climate change shock [MW]
Δk	additional production capacity [MW]
l	intake flow of cooling water [m^3/s]
$\bar{l}$	maximum permissible level of river water for cooling [m^3/s]
L	river flow [m^3/s]
μ_D	drift coefficient Brownian motion
p_t	electricity price at time t [$/GWh]
π	daily operating profits [$]
π_O	daily operating profits, open cooling [$]
π_C	daily operating profits, closed cooling [$]

Π	plant net present value (NPV) [$]
$\Pi^*\,(\hat{\Pi})\,[\tilde{\Pi}]$	plant NPV, fully informed (ignorant) [somewhat ignorant] operator [$]
$\Delta\Pi$	impact of climate change on plant value with adaptation [$]
$\Delta\Pi_{CC}$	impact of climate change on plant value without adaptation [$]
$\Delta\Pi_{info}$	value of climate change information [$]
q	probability of positive price shock
Q	heat [MJ/s]
Q_w	waste heat [MJ/s]
r	interest rate
R	expected revenue stream from retrofitting [$]
ρ	fresh water density [kg/m^3]
σ_p	electricity price variance parameter
t, τ	time indices
$t_1\,(t_2)$	retirement date of current plant (of future plant)
t_C	date of climate change impact
t_A	date of climate adaptation investment
T	temperature of river water [K]
T_D	average water intake temperature according to plant design [K]
T_{max}	maximum permissible temperature of cooling water [K]
ΔT_{max}	maximum permissible increase of cooling water temperature [K]
θ_P	price jump coefficient
θ_c	climate scenario c
V	expected additional operating profits from option to retrofit [$]
W	expected operating profits without adaptation [$]
x	price uncertainty parameter
ξ	cooling technology correction factor for cooling demand [$m^3 \cdot K/MJ$]
y	electricity output [MW]
y_d	daily electricity production [GWh]

Appendix B. Adaptation

Appendix B.1. Adaptation in the short run - a simple model of electricity production

To transform our static optimization problem with multiple choice variables into a single variable problem, we impose $\Delta T = \overline{h}$ and we note that, by rearranging eq. (6) with the use of $e = \frac{y}{\eta}$ and $Q_w = (1-\eta)e$, that $e = \frac{1}{1-\eta}\frac{1}{\xi}\overline{h}l$. We can then write the Lagrangian associated with this problem as

$$\mathcal{L} = \left(p - \frac{c}{\eta}\right)\frac{\eta}{1-\eta}\frac{1}{\xi}\overline{h}l + \lambda_k\left(k - \frac{\eta}{1-\eta}\frac{1}{\xi}\overline{h}l\right) + \lambda_e\left(\overline{e} - \frac{1}{1-\eta}\frac{1}{\xi}\overline{h}l\right) + \lambda_l\left(\gamma L - l\right)$$

The solution l^* consists of a number of different regimes:

1) Capacity constrained ($\lambda_k > 0$ and $\lambda_e = \lambda_l = 0$).
Plant capacity limits production, that is, $y = \eta e = k$ with $e < \overline{e}$. In this regime, higher water temperature reduces plant efficiency and increases the demand for cooling water and fuel. The operator keeps production at maximum capacity by increasing fuel input and water intake until a constraint on water intake of fuel input is hit, or the plant's profit margin turns negative.
2) Fuel constrained ($\lambda_e > 0$ and $\lambda_k = \lambda_l = 0$).
In this regime fuel intake is maximized, $e = \overline{e}$, while production is lower than design capacity due to efficiency loss, $y = \eta\overline{e} < k$. Further increases in temperature ($\overline{h}$ falls) reduce efficiency η, but water flow l can be increased and production maintained net of efficiency loss.
3) Water constrained ($\lambda_l > 0$ and $\lambda_k = \lambda_e = 0$).
The operator is forced to reduce the intake of cooling water, because l is limited due to low river flow or environmental regulations, such that $l = \gamma L$. As a result, $e < \overline{e}$ and $y < \eta\overline{e} < k$. In this regime, severe load reduction may occur, as power output is directly related to the amount of waste heat that can be discharged.
4) Price constrained $\left(p \leq \frac{c}{\eta}\right)$.
If fuel costs exceed the price of electricity, the operator suspends production to avoid losses.

To implement the model numerically, we follow Koch and Vogele (2009) and assume the following correction factors for once-through (O-T) cooling and closed-cycle (C-C) cooling tower technology respectively, $\xi_{OT} \equiv \frac{1-\alpha}{\rho \cdot C_p}$ and $\xi_{CC} \equiv \frac{(1-\alpha)\cdot(1-\epsilon)\cdot EZ}{\rho \cdot C_p}$, where α is the share of waste heat not discharged by cooling water, ρ represents freshwater density [kg/m^3], C_p equals specific heat capacity of water [MJ/kg K] and ϵ is the share of waste heat released into the air. If a power plant uses a cooling tower, additional water will be necessary in order to avoid salinization caused by water evaporation. To control for this we introduce a densification factor denoted by EZ (see Rubbelke and Vogele (2011)). Since we lack a detailed perspective on dry cooling technology, we set $\xi_{dry} \to \infty$; the implicit assumption here is that production becomes completely independent of ambient conditions. Although it is an extreme assumption, it fits with the paper's objective to make the best possible case for power plant adaptation by means of forecasting.

Appendix B.2. Adaptation in the long run - two benchmark adaptation models

The operator maximizes (13). From the resulting first-order condition, we solve for t_A^*. Let us refer to $s_t \equiv p_t(k_A - k_0)$ and $s_t^C \equiv p_t(k_A - k_C)$ as the net instantaneous benefits from adaptation during the pre climate change phase ($t \in [t_0, t_C)$) and during the post climate change phase ($t \in [t_C, t_1)$) respectively. Furthermore, let rI be the cost of capital and define $S_0(t, t_C) \equiv \left(\int_t^{t_C} s_v e^{-r(v-t)} dv\right)$ and $S_1(t, t_1) \equiv e^{-r(t-t_A)}\left(\int_t^{t_1} s_v^C e^{-r(v-t)} dv\right)$ as the cumulative net adaptation benefits for the pre and post climate change phases. To aid the proof of Proposition 2, let us characterize optimal adaptation by a fully informed operator and an ignorant operator in Lemma 1-a and Lemma 1-b respectively:

Lemma 1-a. Adaptation by a Fully Informed Operator.
A. The informed operator of an asset with finite lifespan decides to adapt:
(1) immediately, $t^*_{A,1} = t_0$, *if* $s_{t_0} > rI$ *and* $S_0(t_0, t_C) + S_1(t_C, t_1) > I$.
(2) before climate change, $t^*_{A,2} = t_0 + \frac{1}{g_p}\ln\left(\frac{rI}{s_{t_0}}\right) < t_C$, *if* $s_{t_0} < rI = s_{t^*_{A,2}} < s_{t_C}$ *and* $S_0\left(t^*_{A,2}, t_C\right) + S_1(t_C, t_1) > I$.
(3) at the time of impact, $t^*_{A,3} = t_C$, *if* $s_{t_C} < rI < s^C_{t_C}$ *and* $S_1(t_C, t_1) > I$.
(4) after climate change, $t^*_{A,4} = t_0 + \frac{1}{g_p}\ln\left(\frac{rI}{s^C_{t_0}}\right) \in (t_C, t_1)$, *if* $s^C_{t_C} < rI = s^C_{t^*_{A,4}}$ *and* $S_1\left(t^*_{A,4}, t_1\right) > I$.
B. The informed operator never adapts in all other cases.

Lemma 1-b. Adaptation by an Ignorant Operator.
A. The ignorant operator of an asset with finite lifespan decides to adapt:
(1) immediately, $t^{**}_A = t_0$ *if* $s_{t_0} > rI$ *and* $S_0(t_0, t_1) > I$.
(2) at $t^{**}_A = t_0 + \frac{1}{g_p}\ln\left(\frac{rI}{s_{t_0}}\right) < t_1$ *, if* $s_{t_0} < rI = s_{t^{**}_A}$ *and* $S_0(t^{**}_A, t_1) > I$.
B. The ignorant operator never adapts in all other cases.

Proposition 2. No-Regret Benefits and Costs and the (Ir)relevance of Climate Change Information.
Proof. Using Lemma 1-a and Lemma 1-b, we can formally characterize the different regions (full overlap, strong underadaptation and weak underadaptation) in (t_1, I)-space:

- *Full overlap.*
  (i) $t^{**}_A = t^*_{A,2} = t_0$, *iff* $I \leq \frac{s_{t_0}}{r}$ *and* $I \leq S_0(t_0, t_1)$.
  (ii) $t_0 < t^{**}_A = t^*_{A,2} < t_C$, *iff* $\frac{s_{t_0}}{r} < I < \frac{s_{t_C}}{r}$ *and* $I \leq S_0(t^{**}_A, t_1)$.
- *Strong Underadaptation.*
  (iii) $t^*_{A,2} < t_C$, *iff* $\frac{s_{t_0}}{r} < I < \frac{s_{t_C}}{r}$ *and* $S_0(t^{**}_A, t_1) < I \leq \left[S_0(t^{**}_A, t_C) + S_1(t_C, t_1)\right]$
- *Weak Underadaptation.*
  (iv) $t^{**}_A > t^*_A \geq t_C$, *iff* $\frac{s^C_{t_C}}{r} < I < \frac{s_{t_1}}{r}$ *and* $I \leq S_0(t^{**}_A, t_1)$.
- *Strong Underadaptation.*
  (v) $t^*_A \geq t_C$, *if (a)* $\frac{s_{t_1}}{r} < I < \frac{s^C_{t_1}}{r}$ *and* $I \leq S_1\left(t^*_{A,4}, t_1\right)$, *if (b)* $\frac{s^C_{t_C}}{r} < I < \frac{s_{t_1}}{r}$ *and* $S_0(t^{**}_A, t_1) < I \leq S_1\left(t^*_{A,4}, t_1\right)$.

There are two cases to consider:

I. Adaptation with no-regret benefits, $k_A > k_0$. Straightforward inspection of the regime conditions reveals how a favorable parameter shift (decrease in rI and/or increase in t_1) makes climate change information less relevant for policy makers. For example, in all regimes a decrease in rI can induce a move to one of the lower ranked regimes. For example, in regime (v) a decrease in rI can induce a move to either regime (i), (ii), (iii) or (iv). A shift to regime (i) or (ii) would make climate change information irrelevant for policy makers.

II. Adaptation with no-regret costs, $k_A \leq k_0$. In this case we find that adaptation, if deemed efficient, always occurs post climate change, $t^*_A \geq t_C$, while the ignorant manager never adapts. Starting from a no adaptation regime, a sufficiently large favorable parameter shift can then induce the informed policy maker to adapt, making climate change information ceteris paribus more relevant.

■

Proposition 3. Price Uncertainty and the (Ir)relevance of Climate Change Information.

Proof. (i) We solve this game against nature via backward induction. The optimal second period strategies of (a) always invest, (b) invest in high state only and (c) never invest, arise under (a) $I < p^L \Delta k$, (b) $p^L \Delta k < I < p^H \Delta k$ and (c) $p^H \Delta k < I$ respectively, where we defined $\Delta k \equiv (k_A - \theta_C k_0)$.

There are two potential investment thresholds that shape the first-period solution. Let us define I_w and I_n respectively as the first-period investment threshold that makes the operator indifferent between investing and waiting, that is, $\Pi(0; I_w, x) = \Pi(1; I_w, x)$, and the first-period threshold that makes the operator indifferent between never investing or investing now, that is, $\Pi^n(0; I_n, x) = \Pi(1; I_n, x)$, where n is a mnemonic for "never invest". These solutions read:

$$I_n = p\,(k_A - k_0) + \left(\frac{1}{1+r}\right) p^e \Delta k \tag{B.1}$$

$$I_w = \frac{1}{1 - \frac{q}{1+r}} I_n - \frac{\frac{q}{1+r}}{1 - \frac{q}{1+r}} p^H \Delta k \tag{B.2}$$

From these two equations and the fact that only p^H depends on x, with $\frac{\partial p^H}{\partial x} > 0$, it follows immediately that there exists a unique x^* for which $I_w(x^*) = p^H(x^*) = I_n$, such that a waiting region is part of the solution for all $x > x^*$,

$$\Pi^* = \left\{ \begin{array}{ccc} \Pi(1) & , & I < I_w \\ \Pi(0) & , & I_w \leq I < p^H \Delta k \\ \Pi^n(0) & , & p^H \Delta k \leq I \end{array} \right\}$$

while such a waiting region is absent for all $x \leq x^*$,

$$\Pi^* = \left\{ \begin{array}{ccc} \Pi(1) & , & I < I_n \\ \Pi^n(0) & , & I \geq I_n \end{array} \right\}$$

Since $\widehat{\Pi} = \Pi^n(0)$ it then follows immediately that

$$\frac{\partial\left(\Pi^* - \widehat{\Pi}\right)}{\partial x} = \frac{\partial\left(\Pi^* - \Pi^n(0)\right)}{\partial x} = \left\{ \begin{array}{c} \frac{\partial \Pi(0)}{\partial x} = \frac{q}{1+r} p \Delta k > 0 \quad , \quad \left(I_w \leq I < p^H \Delta k\right) \cap (x > \overline{x}) \\ 0 \quad , \quad \text{all other conditions} \end{array} \right\}$$

which proofs $\frac{\partial\left(\Pi^* - \widehat{\Pi}\right)}{\partial x} \geq 0$. Second, for any parameter configuration waiting is more likely to be the optimal strategy if x is larger since $\frac{\partial p^L}{\partial x} < 0$, $\frac{\partial p^H}{\partial x} > 0$ and $\frac{\partial I_w}{\partial x} = -\frac{\frac{q}{1+r}}{1-\frac{q}{1+r}} p \Delta k < 0$.

(ii) Let us refer to variables of the somewhat ignorant manager with a tilde ($\tilde{}$). There are 3 configurations to consider. First, consider $x < x^* < \tilde{x}$. In this case we always have $\frac{\partial\left(\Pi^* - \widetilde{\Pi}\right)}{\partial x} = 0$. Second, consider $x^* < x < \tilde{x}$. In this case it becomes possible that the informed operator waits while the somewhat ignorant operator never invests, i.e., $\frac{\partial\left(\Pi^* - \widetilde{\Pi}\right)}{\partial x} = \frac{\partial \Pi(0)}{\partial x} > 0$. Third, consider $x^* < \tilde{x} < x$. In this case it is possible that either the informed or somewhat ignorant manager waits, while the other one does not, such that $\frac{\partial\left(\Pi^* - \widetilde{\Pi}\right)}{\partial x} = \frac{\partial \Pi(0)}{\partial x} > 0$ or $\frac{\partial\left(\Pi^* - \widetilde{\Pi}\right)}{\partial x} = -\frac{\partial \Pi(0)}{\partial x} < 0$. Finally, note that as under (i) the size of the waiting region increases for both type of operators if x increases, such that for a larger range of parameters the payoffs of the informed and somewhat ignorant operator become similar. ■

Appendix C. Projections of river flow and water temperature

The impact of climate change on the usable capacity of selected thermoelectric power plants was calculated by using our simple representation of electricity generation (see Appendix B.1), forced with daily river flow and water temperature projections. These projections were produced on daily time step and 0.5^o x 0.5^o spatial resolution for Europe and the United States with the physically-based hydrological model VIC (Liang et al., 1994) and water temperature model RBM (Yearsley, 2009). These models simulated observed river flow and water temperature conditions realistically (van Vliet et al. (2012b)); van Vliet et al. (2012a)) and were subsequently forced with bias-corrected output from five different general circulation models (GCMs) (MIROC-ESM-CHEM, IPSL-CM5A-LR, HadGEM2-ES, NorESM1-M and GFDL-ESM2M) for both the representative concentration pathway (RCP) 2.6 (van Vuuren et al., 2011) and 8.5 (Riahi et al., 2011) for 1971-2099. This resulted in 10 climate change experiments. Both RCP2.6 and RCP8.5 were selected to capture the largest range of uncertainties in radiative forcing under future greenhouse gas emissions. For details of the bias-corrected climate scenarios see Hempel et al. (2013).

The hydrological-water temperature model runs were performed on daily time step for the full time slice 1971-2099. Our analysis only relies on the time slice 2011-2080. To account for uncertainties in GCM output, the multi-model (GCM) average in river flow and water temperature for the five selected GCMs for RCP2.6 and RCP8.5 were calculated. The no-climate-change (or status quo) scenario is constructed by assuming that the control period 1971-2000 repeats itself for three consecutive periods over the 2001-2090 interval, and then carving out the selection 2011-2080.

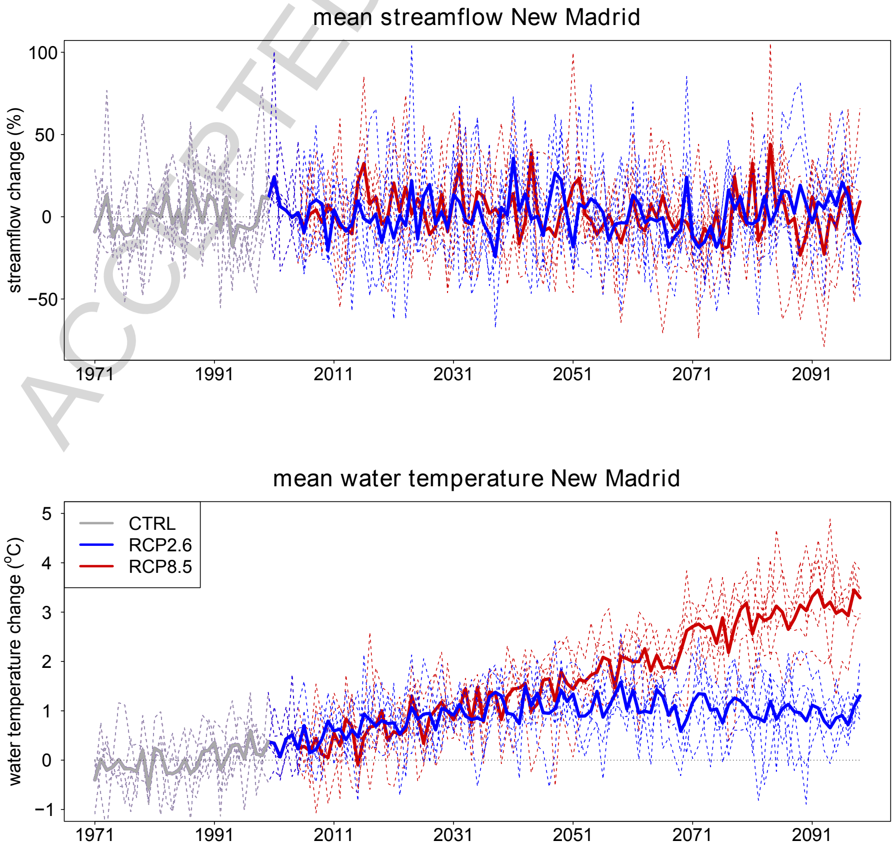

Figure C.11: Projections of streamflow and water temperature for the New Madrid coal plant (1971-2099).

Appendix D. Numerical analysis

To determine (expected) plant profits under climate change, with and without adaptation, we first calculate projections for fuel consumption, output and profits. We calibrate the design temperature T_D, that is, the average ambient temperature at which engineers expect the plant to operate, by taking a simple mean of the water temperature projections that are relevant for the time period in which the plant under consideration became operational, that is, 1971-1980 and 1991-2010 for the New Madrid (1972) and Civaux (2002) power plant respectively. For the new-to-be-build plants in 2031 (New Madrid) and 2041 (Civaux), we take the 2021-2040 and 2031-2050 mean respectively from the climate scenario that is envisioned by the investor (status quo, RCP2.6 or RCP8.5).

We fix the plant efficiency sensitivity parameter at $\delta = 0.002$, which implies that a plant that operates at 15 degrees Celsius above its design temperature, becomes 3% less efficient. Our value is in the middle of the range presented by Durmayaz and Sogut (2006), but well below the empirical estimate of 0.004-0.007 presented by Linnerud et al. (2011).

At any given day, the power plant operates in one of three production regimes (capacity constrained, fuel constrained or water constrained). We use daily projections for river flow L_t and water temperature T_t^w over the period 2011-2080 and combine them with data on power plant characteristics and our estimates of T_D and δ to solve for plant output y_t and plant fuel consumption e_t. Since at least one constraint is binding, the optimal values y_t^* and e_t^* are then constructed by taking the minimum value across the three regimes. These projections of y_t^* and e_t^* are then combined with (expected) price paths for electricity and fuel to generate projections of future operating profits. If these are negative, the plant shuts down.

Future profits are calculated for both the old plant with once-through cooling and the new power plant with a cooling tower system. Lifetime operating profits for stage 1 (W_1) and for stage 2 $\left(W_2^O \text{ and } W_2^C\right)$ then follow directly. For each time period t we determine the instantaneous reward from retrofitting, which is equal to the expected, additional profits that are obtained once a cooling tower is installed or an alternative heat sink is created. We assume that a retrofitted plant can switch between cooling systems in order to maximize profits, thereby introducing no-regret benefits that operators capture under any climate scenario. For both Stage 1 and Stage 2, we determine the value functions V_1 and V_2 by means of backward recursion, working backwards from the last period to the first period.

Following (Guo and Costello, 2013), we determine the value of adaptation (or the value of climate change information) by relying on a simple accounting methodology, which states that the value of adaptation is equal to the present value under climate change with full information minus the present value under climate change without full information. Therefore we also calculate output, fuel consumption, profits and the appropriate value functions under the assumption that e.g., the true scenario is the RCP8.5 climate scenario, whereas the operator incorrectly believes the true scenario is the status quo scenario of no climate change. Since decisions based on incorrect information can never improve plant profits, the value of adaptation must be (strictly) positive. Similarly, we can decompose the value of adaptation in an intensive margin component and an extensive margin component by assuming that the operator takes optimal decisions with respect to one particular dimension, but suboptimal decisions regarding another.

When the price of electricity or fuel is a stochastic variable, we solve the resulting stochastic dynamic programming problem in Matlab by using a binomial tree approach. Although more advanced numerical methods are surely available, the hallmark feature of a tree approach, i.e., flexibility, is required in order to deal with the fact that output y_t and fuel consumption e_t are time-varying. The parameters of the stochastic process should be chosen in such a way to ensure that it approximates the continuous time geometric Brownian motion and to ensure rapid convergence when picking increasingly smaller time steps. To this end, we use the Tian moment matching model. In Tian's model, the three parameters that are associated with the random walk with drift, that is, ″up″, ″down″ and ″probability up″, are chosen to ensure that the first three moments of the continuous time stochastic process are matched.

Highlights

- We analyze adaptation to climate change by thermal power plants.
- A numerical investment model is applied to a coal plant and a nuclear power plant.
- The numerical analysis is based on climate and hydrological projections.
- Climate change information has a relatively small effect on a power plant's NPV.
- Uncertainty and no-regret benefits lower the value of climate change information.

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