Climate Change and Corporate Investments: Evidence from Planned Power Plants

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Abstract

How does global warming affect firms' activities? We consider this issue from the perspective of the electricity producing industry. Warmer temperatures increase the demand for air conditioning, the use of which fluctuates substantially over time, making investments in "flexible" power plants that can be turned on quickly and at low cost more valuable. Using an international sample of planned power plants, we estimate that hotter weather in a region leads utilities to increase their investments in flexible power plants. This effect appears to be driven by long-term changes in climate rather than abnormally high temperatures that occur over a short period. While these results are specific to the electricity industry, it is likely that climate change will require similar adjustments of firms' assets in other industries as well.

JEL classification: G30, G31

Key words: Climate change, global warming, firm investment, electricity generation, power plants

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1. Introduction

Climate change has become one of the most important issues of our time, impacting many aspects of human life (Nordhaus, 2019). From a corporate perspective, a changing climate can affect the demand for firms' products as well as their optimal method for producing these products. To change methods of production, firms potentially have to acquire different assets from the ones they currently own. Therefore, climate change could lead firms to increase their investments, especially those involved with the new method of production. However, theory is ambiguous on this point. There is much uncertainty about both the extent of warmer climates and future regulatory responses to it. Climate change could increase the real option value of waiting to invest (McDonald and Siegel, 1986; Dixit and Pindyck, 1994), so lead to fewer investments at any point in time. The extent to which climate change affects firms' investments is an empirical issue that the literature has not yet addressed.

One industry for which the effect of climate on investments is likely to be substantial is the electricity industry. Demand for electricity is strongly influenced by weather (Pérez-González and Yun, 2013), largely because hot temperatures increase the demand for air conditioning, which is powered by electricity. Air conditioning use varies both seasonally and intra-day, increasing substantially during the daytime in summer months. The climate changes caused by global warming make abnormally hot weather more common (Diffenbaugh, 2020). Hotter weather that leads people to use more air conditioning makes "flexible" electricity-generating plants particularly valuable. Such plants have fast start times and low start cost, so they can be switched on easily when hot weather leads to high electricity demand. Since electricity demand affects wholesale prices, flexible plants are not only essential for grid stability but also more profitable for firms when abnormally hot weather becomes more common.

We evaluate the way in which climate change affects electric utilities' investments in new power plants. We rely on a database about global plant-level investments assembled from *Platts World Electric Power Plants.* Our sample consists of 258 publicly traded electricity-generating firms which are active in 45 deregulated wholesale electricity markets in 38 countries between 2000 and 2016. These firms operate 34,844 power plants, and have plans to construct 5,002 new plants, of which 1,598 are flexible plants (gas, oil, pump-storage), 673 inflexible plants (coal, nuclear, lignite), and 2,537 renewable plants).[1] Their total capacity is more than 1,200 gigawatt (GW), which exceeds the existing capacity in the United States and corresponds to investments of more than 1,500 billion US$.

The electricity industry is a natural place to measure the effect of climate change on firms' investments for a number of reasons. First, it is an industry for which demand fluctuates with the weather, so a changing climate potentially has a substantive impact on firms' operations. Second, demand for electricity is immediately reflected in prices in the wholesale market for electricity, so it is possible from wholesale price data to infer the level of demand at any point in time in any region. Third, we can observe planned power plant investments of firms and can gather detailed data on these investment projects. These data allow us to understand these firms' investments at a much more granular level than in most studies that measure investments using Capital Expenditures (e.g., Giroud, 2013; Harford and Uysal, 2014). In particular, our data cover power plant projects at the planning-stage, so we know exactly when a firm decides to construct what type of power plant at which location. The type of plant tells us its flexibility, i.e., the necessary time and cost of switching a plant on and off. And the locational information allows us to identify the effect of changes of local weather conditions on investment.

We estimate the way in which investments in flexible plants depend on region-specific changes in abnormally hot weather. We measure hot weather relative to the historical average in a region. In particular, the variable we use in the firm-level investment regressions is calculated as the fraction of days between years t-3 and t-1 that would have been classified in the top one percent of days ranked by temperature in the same region between 1951 and 1980. The identification in these models comes from local variation in temperature changes over time, which is exogenous to firms making investment decisions.

We find a positive relation between this measure of region-specific changes in hot weather and investments in flexible power plants, in a number of models that exploit changes of hot days across markets and over time. The estimates imply that the planned capacity of flexible plants, scaled by the total existing

[1] These numbers refer to power plant units since different units of a plant can be constructed at different time and use different production technologies.

capacity, increases by slightly more than one percentage point if one percent more days are classified as abnormally hot, which corresponds to a relative increase of approximately 15 percent. The findings are similar if we control for firms' market power, gas prices, spark spreads, or environmental regulations. The firm-region-level analysis enables us to include a set of high-dimensional fixed effects such as firm by year and market by year fixed effects. Specifications that include these high-dimensional fixed effects show that this positive sensitivity of investment to changes in weather is not likely to be driven by any time-variant or time-invariant factors on the firm, country, or electricity-market level.

An important issue in interpreting the investment-weather sensitivity is the extent to which the changes in investment behavior are a reaction to short-term fluctuations in weather, or whether firms are adjusting the composition of their assets in response to long-term changes in climate. To distinguish between these explanations, we rely on climate forecasts that are assembled by different climate research groups around the world for the Coupled Model Intercomparison Project (CMIP) 5. These forecasts of the future climate are based on sophisticated global coupled ocean-atmosphere general circulation models. We use the geographically downscaled version of the models' high-resolution outputs to measure the anticipated future change in summer days, defined as days with a maximum temperature above 25 degree Celsius, in a particular electricity market region.

Our estimates indicate that that regions where the anticipated climate change is larger have a higher investment-weather sensitivity. This finding implies that in regions in which more summer days are expected in the future, firms respond by increasing their investments in flexible power plants. In contrast, when the hot days are more likely to be random fluctuations than an indication of more hot days in the future, firms adjust their investments less. We also consider the uncertainty in the CMIP5 forecasts, since when uncertainty is higher, the option value of waiting to invest increases. We estimate that a higher prediction uncertainty leads to a lower investment-weather sensitivity. This result indicates that uncertainty about the extent of the future climatic change increases firms' option value of waiting, which is in line with theoretical models which assume irreversible investments (McDonald and Siegel, 1986; Dixit and Pindyck, 1994)[2] and previous results for political uncertainty (Julio and Yook, 2012).

We argue that energy utilities would increase their investments in flexible power plants in response to warmer temperatures is because of changing demand patterns for electricity. Due to more use of air conditioning when the weather is hotter, electricity demand tends to be higher in summer months and during noon and afternoon hours when temperatures are highest. As a consequence, climate change and global warming will lead to more peak demand for electricity and a greater desire for flexible power plants that can be switched on and off quickly and at low cost to meet consumption peaks at low cost (Auffhammer et al., 2017). In deregulated electricity markets, higher peak demand for electricity is also likely to lead to higher electricity prices, which in turn make flexible plants more valuable for energy utilities.

We perform a series of tests designed to verify whether this mechanism is likely to be the driver of our findings. First, we calculate the investment-weather sensitivity separately for different power plant types. This argument predicts that there should be positive weather-sensitivities only for flexible plants if higher peak demand is indeed the channel behind our results. For inflexible plants, the argument predicts insignificant or even negative sensitivities since those production technologies have high fixed cost and need to run most of the time so cannot be used to satisfy demand peaks. Renewable plants have intermittent production, which reduces their ability to satisfy demand peaks because they cannot be actively switched on if the demand surges. We find a positive investment-weather sensitivity only for flexible gas-fired plants, marginally negative sensitivities for nuclear plants, and statistically insignificant ones for all other plant types (e.g., oil, coal, hydro, wind, solar).

As second mechanism test, we use data on hourly electricity prices in 38 markets to investigate the way in which hot weather affects prices. Consistent with the notion that higher temperatures increases both the average demand for electricity and its volatility due to more pronounced day-night differences, we find that hot weather on a particular day leads to a higher and more dispersed electricity price on that day. When

[2] However, models that consider time-to-build, which is typically years for power plants, find that the uncertainty-investment relation is considerably weaker or, in extreme cases, even reversed (Bar-Ilan and Strange, 1996).

we focus on the annual distribution of daily electricity prices, we find that average prices increase with hot weather. This effect is mainly driven by the upper tail of the price distribution since we find the strongest effects for the 90% and 95% quantile of the electricity prices. These results indicate that intraday and seasonal variation in electricity prices increase with the incidence of hot weather, making flexible power plants more valuable for firms (D'Acunto et al., 2018). Due to their low fixed cost, short start times, and low start cost, they can be switched on whenever the electricity price exceeds their production cost. We find similar results if we analyze the annual distribution of the monthly electricity demand: the average demand increase, and this increase is mainly driven by higher peak demand for electricity.

The third mechanism test focuses on variations in the use of air conditioning across regions. The conceptual link between hot weather, electricity demand, and prices is conditional on the usage of air conditioning in an electricity market. Therefore, we would not expect any impact of hot weather on investments in flexible plants for regions in which air conditioning is not common. Since there is, to the best of our knowledge, no comprehensive data available on the prevalence of air conditioning use for across countries, we rely on three variables that potentially proxy for the use of air conditioning: cooling demand due to climatic conditions, economic development, and the sensitivity of electricity prices to hot days. In line with our expectations, we find that the positive impact of hot weather on investments in flexible power plants is only existent in regions with medium or high cooling demand and GDP per capita. We calculate the sensitivity of electricity prices to hot weather conditions based on daily data on temperatures and electricity prices. We find that the impact of hot weather on flexible investments is most pronounced in markets in which electricity prices react strongest to hot weather. Thus, all three proxies provide evidence for the mechanism that hotter weather leads to more air conditioning, which in turn affects electricity demand and prices and makes flexible plants more attractive for energy utilities.

As a final test, we study the role of firms' operating flexibility in more detail. We measure firms' operating flexibility as their existing flexible production capacity (gas, oil, or pump storage plants) relative to the sum of flexible and inflexible capacity. When we analyze which firms invest in flexible power plants as response to hotter weather, we find that the building-up of flexible production capacity is stronger in firms with a low level of existing flexibility. These results suggest that especially inflexible firms react to changing weather conditions by adjusting their production portfolio towards more operating flexibility.

Although this study focuses exclusively on energy utilities, our results potentially have implications for other industries as well. The impact of hotter weather is likely to vary by industry and is undoubtedly different from the electricity generating industry we study here because of the unique relation between energy demand and weather. However, firms from many industries will have to cope with adjustments of their production process,[3] disruptions to their supply chains,[4] less predictable consumer demand,[5] shifts of consumer preferences,[6] or new regulations[7]. It seems likely that firms facing these issues from climate change respond in a manner similar to that which we have documented for electric utilities.

Our analysis extends the literature on weather, climate risk and finance. In their early works, Hirshleifer and Shumway (2003) find a positive relation between sunshine and market returns. Pérez-González and Yun (2013) use energy utilities to measure the value of risk management with weather derivatives. Giroud et al. (2012) use unexpected snow to study how debt restructuring affects firm performance. A more recent example is Krueger, Sautner, and Starks (2020), who explore how climate change affects institutional investors' risk perception. Hong, Karolyi, and Scheinkman (2020) provide a recent overview on this to a new and emerging line of research. We provide novel evidence that changing weather conditions affect the market demands and as a consequence the investments decisions of energy utilities. By doing so, our paper also adds to the finance and product market literature, which documented that product markets characteristics affect financing decisions (Kovenock and Phillips, 1997; D'Acunto et al., 2018) and payout policy (Hoberg, Phillips, Prabhala, 2014).

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[3] Many firms in the food production industry need to adjust their production process to changing climatic conditions (https://www.theguardian.com/environment/2012/sep/19/climate-change-affect-food-production).

[4] Extreme weather could trigger a beer shortage because breweries could face shortages in their supply of barley (https://www.nature.com/articles/d41586-018-07015-7).

[5] Sales of beer or bottled water is strongly linked to weather conditions during the summer months in many countries (https://www.thelocal.no/20180719/norwegians-set-records-for-beer-consumption-during-hot-summer).

[6] The tourism industry needs to adjust its "assets" because consumers' demand shifts to different regions (http://www.ktoo.org/2014/08/04/report-alaska-tourists-may-shift-new-areas-climate-change).

[7] Chinese steel producers have to cope with tougher environmental regulations to reduce pollution levels (http://www.reuters.com/article/china-steel-environment-idUSL4N0VE3R820150204).

2. Data and Methods

2.1. Sample of energy utilities

To construct a global sample of energy utilities, we start by combining lists of active and inactive public utility companies from *Thomson Reuters*. The sample covers the years 2000 to 2016, which is the period for which we can obtain the necessary annual data on firms' production assets. After cleaning the sample and filtering those firms which operate in regions with wholesale markets for electricity,[8] we end up with 258 energy utilities. For the construction of our dataset, we consider all electricity market regions in which a firm owns at least 100 MW of capacity. On average, every firm is active in about three different electricity markets. These sample firms participate in 45 electricity market regions from 38 countries, and operate 34,844 unique power plant units.

2.2. Measuring power plant investments

We obtain data on power plants from the *Platts World Electric Power Plant* database. These data contain information on individual power plant units around the globe, including their production technologies, capacities, geographic locations, start dates of commercial operation, and their owners/operators. Using the annual version of this database for all years between 2000 and 2016, we manually match each power plant unit to the energy utilities sample.[9] About one-third of the worldwide electricity production capacity is from our sample firms; the remainder is produced by utilities that are not publicly listed, or from plants in non-deregulated regions without wholesale markets for electricity and are excluded from our sample for this reason. Importantly for our purposes, this database does not only cover completed power plants, but also planned construction of new plants.[10]

[8] First, we eliminate all firms without a primary security classified as equity. Second, we wish to consider only companies that focus on the generation of electricity. To ensure that other companies are not included, we rely on firms' SIC and ICB codes, their business description obtained from *Capital IQ*, and additionally conduct manual research on their business lines. Finally, we eliminate firms that do not have any operations in regions with wholesale markets for electricity and firms that use only renewable energy sources for electricity production.
[9] We use the annual version of the database because historical owner/operator information is not included.
[10] These are plants with the status code PLN, which means planned (still in planning or design). Platts states that "the decision to include new power projects in the WEPP Data Base is […] made on a case-by-case basis. Key determinants

These data on existing power plants as well as planned power plant projects allow us to construct our measures of investment. Our main dependent variable, *Flexible Investments*, is defined as planned construction projects of flexible power plants (in megawatt, MW) of firm *i* in electricity market region *m* and year *t*, scaled by the capacity of existing power plants (in MW) of the same firm *i* in the same region *m* and year *t*. The variable is set to one if the planned capacity exceeds the existing capacity.

Climate change and hotter weather are likely to increase the value of flexible power plants relative to other types because their output can be adjusted at low cost during times of high air conditioning use in noon and afternoon hours of summer months. We classify power plants using gas (combined cycle gas turbines, gas turbines, gas-fired reciprocating engines), oil, or pump storage as production technology as flexible, and use the capacity of these plants that are planned, relative to the existing capacity of the firm in the same region, as our measure of flexible investment. Gas and oil-fired plants can start very quickly, typically within minutes, have low start cost, and comparatively low fixed cost and construction cost per MW capacity which allows their owners to operate them only during times of peak demand (Reinartz and Schmid, 2016) .[11] Pump storage plants can store electricity by pumping water upwards during times of low demand. When demand is higher, they use the stored potential energy of the water to generate electricity.

For robustness, we also consider alternative approaches to measure the flexibility of a power plant. First, we create a dummy variable that equals one if firm *i* has any planned flexible power plant projects in region *j* and year *t*. Second, we use the unscaled logarithm of the total capacity of all flexible planned power plant projects of firm *i* in region *j* and year *t*. Third, we consider the number of planned power plants, rather than their capacity, scaled by the number of existing plants. Fourth, we use the logarithm of the number of planned flexible plants.

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in approximate order of importance are: 1) order placement for generating equipment or engineering, procurement, and construction (EPC) services, 2) the status of licensing or permitting activities, 3) funding, and 4) the availability of fuel or transmission access. Projects may also be included even if such data are lacking if there are generalized national or regional policies that are driving power plant development." (*Platts Data Base Description and Research Methodology*, p.19).

[11] See, for instance, Table 2-5 of the "Capital Cost Estimates for Utility Scale Electricity Generating Plants" from November 2016 by the EIA.

Table 1 provides an overview on the planned power plant projects, separately for flexible, inflexible, and renewable plants as well as the single technologies therein. There are 1,598 projects to construct flexible power plant units, which account for a total of 423 GW. The average capacity of planned flexible plant unit is 182 MW. Most planned flexible plant units use gas turbines (614), followed by gas combined cycle turbines (601), pump storage (117), reciprocating generators (115), and oil (87). Combined cycle plants are the largest flexible plants, with an average capacity of 484 MW and reciprocating generators are the smallest, with an average capacity of 11 MW. For inflexible plants, there are 673 projects with a capacity of 485 GW. For renewables, we identify 2,537 projects, mostly in wind and hydro plants, with a combined capacity of 279 GW. In total, there are 5,002 unique investment projects in our sample, which have a combined capacity of 1,221 GW.

2.3. Measuring abnormal hot weather

Our weather data come from the Global Historical Climatology Network (GHCN). We use the daily average temperatures (GHCN-DAILY) to construct our measures of extreme weather. Based on approximately 200 million individual temperature observations at the weather station level, we start by calculating the average temperature in degrees Celsius in each market region and year from 1951 to 2016. A day is classified as hot if its temperature would belong to the one percent hottest days during the base period 1951 to 1980.[12] The variable *Abnormal Hot Weather* is then calculated as the fraction of hot days in a particular year and market minus .01. In the absence of climatic changes, we would expect to classify one percent of days as extremely hot during our sample period 2000 to 2016, so the *Abnormal Hot Weather* variable measures temperature change of a region from the 1951-1980 period.

[12] Hansen et al. 2012 explain they "choose 1951–1980 as the base period for most of our illustrations, for several reasons. First, it was a time of relatively stable global temperature, prior to rapid global warming in recent decades. Second, it is recent enough for older people, especially the "baby boom" generation, to remember. Third, global temperature in 1951–1980 was within the Holocene range, and thus it is a climate that the natural world and civilization are adapted to. We require at least 20 years of non-missing data on the average temperature during this base period.

In our sample, 1.6 percent of days are classified as abnormally hot, which is calculated as the fraction of hot days, that is 2.6 percent, minus the expected fraction of hot days, that is 1 percent (see Table 2). The average values of the hot weather variable across all markets over time are presented in Figure 1. This figure documents that the fraction of abnormally hot days shows an increasing trend since the end of the base period in 1980, since both the linear and the quadratic fits are upward sloping. The average fraction of hot days increases from zero percent in 1980 to 0.5 percent in 1990, one percent in 2000, two percent in 2010, and more than two percent in 2016. These observations clearly indicate that hot temperatures became more common during the last decades.

2.4. Measuring climate change

To link the investment-weather sensitivity to climate change, we rely on climate forecasts from the Coupled Model Intercomparison Project (CMIP). CMIP is a project of the Working Group of Coupled Modelling of the World Climate Research Programme.[13] This project is a framework that is used by different research groups around the globe to forecast the future climate with help of coupled ocean-atmosphere general circulation models. CMIP Phase 5, which we use in our paper, is the most recently completed phase. It started in 2008 as the successor of CMIP Phase 3 and its results became available the following years.

The majority of the CMIP data that we use comes from the Climate Change Knowledge Portal of the World Bank Group. The advantage of this data is that it is downscaled to the country-level, whereas the raw model output has a high spatial resolution. We use the predicted climate change between the base period 1986 to 2005 and the forecast period 2020 to 2039 based on the intermediate emission scenario RCP4.5. Summer days are defined as days with a maximum temperature above 25 degrees Celsius. Since there are multiple electricity markets in the U.S., Canada, and Australia, we cannot use the country-level

[13] Please see https://www.wcrp-climate.org/wgcm-cmip for more details.

data for those regions. Rather, we collect downscaled CMIP5 model output for the largest city of every electricity market in these countries from various sources (see Appendix A for details).

Our first climate change variable, *CC PREDICTION*, captures the extent of the climate change in a region and is calculated as the average predicted change in summer days between the base and forecast period across all available CMIP5 models. Table 2 shows that the CMIP5 models predict that, on average, 12.9 more days will be classified as summer days in the future. Our second climate change variable is *CC UNCERTAINTY*. This variable captures how much the outputs of different CMIP5 models diverge, which we use as a measure of the uncertainty about the extent of the future change in the climate in a particular region. It is calculated as the standard deviation of *CC PREDICTION* across all available CMIP5 models for a particular electricity market region, scaled by the average predicted change in summer days in that region. The average uncertainty value is 0.48, which implies that the standard deviation of climate change predictions is on average about half of the mean.

2.5. Other Variables

Our source for financial variables is *Worldscope*. The financial variable we include in our equations are size (measured as the logarithm of total assets in $US), profitability (EBITDA scaled by total assets), Tobin's Q (market capitalization of equity plus total liabilities scaled by the sum of the book value of equity plus total liabilities), leverage (total debt scaled by the sum of total debt and book value of equity), and cash holdings (cash and short-term equivalents scaled by total assets). We also control for the two country-level variables GDP per capita and inflation rate, which are based on *Worldbank* data, to account for the fact that electricity consumption and economic development can be correlated (Da, Huang, and Yun, 2017). All variables are winsorized at the 1% and 99% levels; their detailed descriptions can be found in Appendix A.

2.6. Descriptive statistics

Table 2 presents descriptive statistics. Panel A shows the descriptive statistics for the firm-market-year sample. This sample, which includes regions in which a firm owns at least 100 MW of production capacity, is used in most of our empirical tests. On average, the planned investments in flexible power plants account for 7.8 percent of the existing capacity of energy utilities. The firm-level variables indicate that the average market share of our sample firms is 6.1 percent. They are comparatively large, with average total assets of about 26 billion US$. In Panels B and C, we show descriptive statistics for the market-year and the market-day sample. These samples, which are independent of our sample firms, are used for different mechanisms tests.

3. Estimating the Sensitivity of Flexible Investments to Abnormally Hot Weather

3.1. Methods

To measure the extent to which firms change their investment policies based on the weather, we estimate equations predicting the likelihood of a particular kind of investment as a function of weather data. Since the mechanism that seems particularly relevant for electricity producing firms is that abnormally hot weather increases the use of air conditioning, which leads flexible investments to be more valuable, we predict the number of planned flexible power plants as a function of *Abnormal Hot Weather*.

We estimate the equations on a firm-market-year sample organized as a panel dataset, covering the electricity market regions of our sample firms in all years in which they operate power plants with at least 100 MW capacity in that region. We use the average of *Abnormal Hot Weather* between years t-1 and t-3 for two reasons. First, the average over three years is a more precise measure for the true temperature distribution than annual values. As robustness tests, we also show the results for alternative windows. Second, the one-year lag accounts for the time between changes in the weather distribution and investment decisions.

Our empirical specifications start with models without any fixed effects, which exploit both variations in weather across electricity markets and over time. We then add year, firm, and firm times market fixed effects. The identification of the weather sensitivity in the latter models is only based on changes of hot weather over time within markets, not differences in weather across markets. We also present results from models with high-dimensional fixed effects that additionally include firm times year fixed effects and country, electricity market, or state times year fixed effects. These models control for all time-variant and time-invariant firm-level and country, market, or state-level factors. Standard errors are double clustered by firms and countries for all firm-level analysis.

3.2. Regression results

We present estimates of the relation between *Flexible Investments* and *Abnormal Hot Weather* in Table 3. Column 1 includes no fixed effects. We add year fixed effects in Column 2, firm fixed effects in Column 3, and firm times electricity market fixed effects in Column 4. In each specification, the estimated coefficient for hot weather is positive and statistically significantly different from zero. This positive coefficient indicates that firms increase their investments in flexible power plants more in regions with a higher increase of the number of hot days. A graphical illustration of this effect can be found in Figure 2, which plots the average flexible investment for hot weather deciles. Consistent with the estimates in Table 3, Figure 2 indicates that there is a positive relation between the variables.

The coefficient on *Abnormal Hot Weather* is between 0.96 and 1.31, depending on which fixed effects are included. These estimates imply that a one-standard deviation change in the frequency of hot days leads to a 2.0 to 2.8 percentage point increase in flexible investment (which is defined as the capacity of planned flexible power plants relative to existing plants). Because the average *Flexible Investment* is 7.8 percent, these numbers translate into a relative increase of 26 to 35 percent. The estimates also imply that *Flexible Investment* increases by 1.0 to 1.3 percentage points with a one percent higher *Abnormal Hot Weather*. This effect is not only statistically significant, but also large enough to be economically relevant.

3.3. Robustness

We next evaluate the robustness of the relation between abnormally hot weather and utilities' investments in flexible power plants. We focus on the model in Column 4 of Table 3 with firm times market fixed effects. First, we include several firm-level or country-level control variables in Panel A of Appendix

B. However, these additional variables have no substantial impact on the coefficient estimate for hot weather.

Second, we consider utilities' market power.[14] Utilities with high market power could conceivably influence electricity price characteristics through their bidding behavior. If the effect of market power occurs more often when there is more extreme weather, then our results could reflect this market power. However, Panel B of Appendix B documents that the relation holds if we exclude firms that account for more than 20 percent, 10 percent, or five percent of the production capacity in a particular market.

Third, we explicitly control for the gas price and spark spread (the difference between the wholesale market price for electricity and cost of producing electricity with gas).[15] If hot weather had for some reason a direct effect on gas prices, our previous results might not capture a direct effect of hot weather on investment because the majority of our flexible plants use gas as fuel (see Table 1). However, the estimates in Columns 1 and 2 of Panel C of Appendix B show that hot weather has a strong positive impact on flexible investments even after controlling for gas prices or spark spreads. Not surprisingly, spark spreads themselves are also linked to flexible investments, with higher spark spreads leading to more gas-fired plants being constructed because of their higher profitability.

Fourth, it could be that a higher increase of hot weather in a particular region leads to a higher awareness for environmental issues and more stringent environmental protection regulations. This logic could lead firms to invest more in flexible gas-fired plants than inflexible coal-fired plants not because of their differences in flexibility, but because gas plants are less detrimental to the environment than coal plants. To evaluate how this potential relationship affects our findings, we control for environmental regulations using the Environmental Policy Stringency Index (EPSI) and the Climate Change Performance Index.[16] The results in Columns 3 and 4 of Panel C in Appendix B present the results if we interact the two

[14] See Rettl, Stomper, and Zechner (2020) for a discussion of competitor effects in energy markets.
[15] The construction of both variables is described in Appendix A.
[16] This EPSI, which is developed by the OECD, "is a country-specific and internationally-comparable measure of the stringency of environmental policy. Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behaviour" (https://doi.org/10.1787/2bc0bb80-en). For the

(centered) indices with *Abnormal Hot Weather*. These specifications allow for different effects of hot weather on investments depending on a region's level of environmental protection. However, effect of *Abnormal Hot Weather* on utilities' flexible investments remains positive and highly significant, indicating that more stringent environmental regulations due to more hot weather is unlikely to cause our main results.

Fifth, we exclude all single markets to make sure that we document a general effect which is not driven by one particular region. Figure 3 illustrates the coefficient estimates for our base specification in Column 4 of Table 3 when we exclude single markets. The coefficient on *Abnormal Hot Weather* remains positive and statistically significantly different from zero, regardless of which market we exclude. This pattern suggests that we document a general effect that is not driven by any particular market.

Appendix C discusses the robustness of our findings to alternative model specifications. To summarize these results, our findings are robust to alternative measurements of hot weather, alternative measurement periods of hot weather, alternative base periods to classify hot days, alternative concepts to measure hot weather, alternative measures of flexible investments, and alternative clustering of standard errors.

3.4. High-dimensional fixed effects

So far, we have shown that our results are robust to controlling for certain firm-level and country-level factors, such as firm size, profitability, gas prices, spark spreads, or environmental regulation. However, there could be other factors that vary across firms or countries for which we cannot control. To ensure that our results are indeed caused by hot weather not by other firm-level factor that correlate with hot weather, we additionally estimate equations that include firm times year fixed effects. These specifications compare investment decisions of the same firm in the same year across different electricity markets. As a consequence, the sample size is slightly smaller (approx. 3,200 vs 5,000 firm-years in the

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Climate Change Performance Index, we use the climate policy rating as of 2019. This dimensions considers climate protection measures taken by governments (https://www.climate-change-performance-index.org/methodology).

equations in Table 3) because we cannot estimate this specification for firms that only operate in a single market.

We present these estimates in Panel A, Columns 1 and 2, of Table 4. No matter if we only include firm times year fixed effects or firm times year plus firm times market fixed effects, the estimates of the coefficients on *Abnormal Hot Weather* are positive and highly significant. Their magnitude is slightly higher than in our baseline specification (1.39 vs. 1.31 and 1.51 vs. 0.96).

To control for any country-level factors, we estimate specifications that include country times year fixed effects. These specifications, which require variations across electricity markets within countries, exploit that there exist multiple markets within the U.S., Canada, and Australia. The results reported in Column 3 of Table 4 indicate that the coefficient estimate for *Abnormal Hot Weather* approximately doubles relative to that reported in the baseline specification (1.98 vs. 0.96). We find a similar coefficient estimate of 2.18 when we include both country times year and firm times year fixed effects in Column 4 of Table 4.

Although the specifications which we presented to this point control for country-level factors, it could still be that factors that vary within countries on the electricity market or state-level affect our results. To address this possibility, we exploit the unique structure of U.S. electricity markets. These markets use nodal pricing whereas nearly all other markets use zonal pricing. Nodal pricing means that the electricity price is determined separately for each node within an electricity market, leading to heterogenous electricity prices within markets. In contrast, in markets with zonal pricing, the electricity price is the same for all locations within the market. As a consequence, local variations in weather and electricity demand can have different effects on prices for each node. Consequently, investment incentives of utilities depend on demand and prices changes at the node, not the market-level in the U.S. For markets with zonal pricing, the demand at a specific location is irrelevant for the utility since there is a uniform, market-wide electricity price.

To exploit local variations in investment incentives, we construct an alternative sample for U.S. firms and aggregate their investments in power plants on the county-level instead of the market-level. There are more than 50,000 nodes in the U.S., so a typical county would have several nodes. This firm-county-year dataset allows us to analyze how local weather variations within markets or even states affect firms' investments. The results are shown in Panel B of Table 4. Column 1 includes firm times market plus market times year fixed effects, thus controlling for all market-level factors. The coefficient in this is positive and highly significant, albeit slightly smaller than in our baseline specification (0.60 vs. 0.96). The results are similar if we add firm times year fixed effects to control for all firm-level factors in Column 2. In Columns 3 and 4, we repeat the previous regressions but use state instead of electricity market fixed effects. The results are similar to those in Columns 1 and 2. Overall, we conclude that omitted factors on the country, electricity market, state, or firm-level are unlikely to affect our results meaningfully.

4. The Impact of Climate Change on the Investment-Weather Sensitivity

The results discussed to this point indicate that abnormally hot weather increases utilities' investments in flexible production plants. However, it is not clear why this effect occurs. New power plants are long-lived assets whose value depends on the weather over their entire life. Consequently, a firm should base its investment decisions on its expectation of future weather pattern. It is possible that abnormally high temperatures today are indications that temperatures will remain high or increase more in the future, and the investment response we observe reflects the changing climate. Alternatively, it could be that utilities change their investments mechanically to current weather, but not incorporating a rational forecast of future climate. The issue is whether utilities plan investments in flexible power plants because of the changing climate or because of short-term fluctuations in weather.

To distinguish between these explanations, we rely on climate forecasts that are assembled by different climate research groups around the world for the Coupled Model Intercomparison Project (CMIP) 5. These forecasts of the future climate are based on sophisticated global coupled ocean-atmosphere general circulation models (see Section 2.4 for a detailed description of the model and data). They represent the state of the art in forecasting climate changes, so are an estimate agents' expectations of future weather patterns.

If the sensitivity of investment with respect to abnormal weather reflects utilities' responses to a changing climate, then investments in flexible power plants should respond more strongly to abnormally hot weather when climate models suggest that today's hot weather is likely to be predictive of future hot weather. In addition, the effect should be stronger when the climate model is more precise in its predictions.[17]

We present estimates of the way that expectations of future climates affect the investment-weather sensitivity in a region in Table 5. We measure the extent of climate change as the predicted annual change in summer days between the base period 1986 to 2005 and the forecast period 2020 to 2039, averaged across all available CMIP5 models. We split the sample into three sub-samples according to the predicted extent of climate change in a region. We estimate investment-weather sensitivities the predicted climate change. The estimates in Column 1 indicate that investments in flexible plants do not depend on hot weather in regions for which the CMIP5 models predict the lowest change in summer days. This sensitivity becomes positive and statistically significant for the medium-climate change regions in Column 2. The coefficient estimates for the sensitivity is even higher in Column 3 (1.53 vs. 1.01), which includes the regions that are most affected by climate change.

In Column 4, we interact *Abnormal Hot Weather* with the logarithm of the predicted change in summer days from the CMIP5 model. The positive, statistically significant coefficient on the interaction term is consistent with the view that the regions where the climate is expected to warm the most are where firms respond to hot temperatures by adding flexible power plants. Column 5 restricts the sample to years after 2005 to avoid an overlap between the sample period and the base period for the calculation of climate changes, and reports similar estimates to those in Column 4. These results suggest that firms respond to hot

[17] An alternative approach would be to estimate the relation between the estimates of climate change and investment directly. The problem with this approach is that we only have one observation for climate change per electricity market and would need to use a purely cross-sectional research design. Since many local factors, such as the availability of natural resources or the electricity market structure, affect investment choices in the cross-section, it is impossible to establish a casual relationship between climate change and investment decisions using this direct approach.

weather by changing their investments when hot weather at one point in time is informative about changes in climate, leading to potentially even hotter weather in the future.

Next, we analyze how uncertainty about climate change affects the investment-weather sensitivity. If the reason why unusually hot weather leads to more flexible investments is that the unusually hot weather changes expectations about future weather, then this relation should be stronger when the forecast of future weather is known more precisely. We measure the accuracy of climate forecasts using the standard deviation of the predicted change in summer day across all available CMIP5 models for a particular electricity market, scaled by the average predicted change in summer days in that region.

The estimates, which are reported in Panel B, suggest that the investment-weather sensitivity is highest in regions with low uncertainty about the future climate change. For medium-uncertainty regions, we also find a positive sensitivity, but the estimated coefficient is lower (0.86 vs. 1.74). For the regions with high uncertainty about climate change in Column 3, the estimated coefficient for the investment-weather sensitivity is even lower (0.56) and not statistically significant. The interaction terms in Columns 4 and 5 also indicate that higher uncertainty about the future climate changes reduces the impact of hot weather on flexible investments, although the interaction term is only statistically significant for years after 2005.

5. The Channel through which Unusually Hot Weather Affects Investments

We have documented that changes in hot temperatures lead firms to increase their construction of new power plants that rely on flexible production technologies. A possible reason why firms invest in flexible generation is that hotter weather conditions affect the demand for electricity and, as a consequence, the value of flexible plants. Demand for electricity is strongly influenced by weather, largely because hot weather increases the demand for air conditioning, which is powered by electricity. Air conditioning use varies both seasonally and intra-day, increasing substantially during the daytime in summer months. Hotter weather that leads people to use more air conditioning makes “flexible” electricity-generating plants particularly valuable. Their fast start times and low fixed costs allow utilities to switch them on when hot weather leads to high electricity demand and off during other times.

To evaluate the extent to which this demand channel is the reason why more hot days lead to increased construction of flexible power plants, we first examine the investment-weather sensitivity separately for every production technology. If the demand channel is the driver behind our results, we expect to find positive sensitivities only for flexible generation technologies. After that, we examine the underlying elements of this demand channel, leading an abnormally high number of hot days to affect electricity demand, prices, and investments in the way we described.

5.1. Technology-specific investment-weather sensitivities

Our detailed information on the planned power plants allows us to estimate the investment-weather sensitivity separately for every production technology. As described earlier, we consider gas-fired and oil-fired plants to be "flexible" because they are able to adjust production to satisfy peak demand due to their quick start times and low fixed cost. Additionally, we consider pump storage generation to be "flexible" because it can be used to smooth demand peaks over time (by pumping water uphill when demand is low and using the stored energy to generate electricity when demand is high). Other conventional generation technologies such as coal, lignite, or nuclear, and hydro plants are typically used to satisfy the base demand for electricity. Because of their high fixed cost and long run-up times, they operate most of the time, regardless of the electricity demand or price.[18] Intermittent plants cannot be actively dispatched, which makes them also unsuitable to satisfy peak demand for electricity.[19] Therefore, we do not expect to find

[18] It is common for operators of those plants to bid a price of zero in the market auction to ensure that their bid is accepted. These relatively inflexible plants are also one of the reasons why negative prices can exist in the electricity market. This happens when it is less costly for the operator to shut down an inflexible plant compared to paying a price for delivering the electricity to the grid.
[19] Solar plants could be helpful to satisfy increased electricity demand for air conditioning if their production is correlated with temperatures. However, the efficiency of solar panels typically decreases when temperatures are very high, and our sample of publicly listed energy utilities does not accurately reflect the overall investments in solar plants, which are often done by smaller firms.

increased investments in inflexible or renewable power plants in response to higher air conditioning use and a higher peak demand for electricity.

We present estimates of technology-specific investment weather sensitivities in Table 6. We find positive and statistically significant investment-weather sensitivities only for gas-fired power plants. Among the gas-fired plants, the sensitivities are positive for combined cycle gas turbines (CCGT) and single cycle combustion turbines (SCCT), but not for reciprocating engines (GFRE). This result is in line with theoretical predictions by Larsen et al. (2017), that most of the additional capacity due to rising temperatures will come from CCGT and SCCT plants. CCGT plants have higher efficiency but slower start times compared to SCCT plants. They can be used to balance seasonal and intra-day variations of electricity demand. SCCT can be used to meet short-term peaks during the day or as reserve margin for unexpected demand shocks (e.g., due to hotter-than-expected weather in a particular hour). GFRE are often used to balance production from intermittent renewable plants like wind or solar, but typically not to cope with higher electricity demand due to more air conditioning.

Since flexible investments are concentrated in gas-fired plants, it is important to note that these plants differ from inflexible plants, especially coal, in a number of ways. First, as we emphasize in this paper, they are more flexible in the sense of faster start/stop times and lower start/stop cost (see Reinartz and Schmid, 2016, for more details). Second, gas-fired plants tend to have higher fuel cost, but lower fixed cost than coal-fired plants. This feature makes them especially suitable for peak-load production because they do not need to run all or most of the time to cover their fixed cost. Third, gas-fired plants emit less CO2 than coal or oil-fired plants. Theoretically, their more environmental-friendly electricity production could provide an alternative channel why utilities invest in gas-fired plants as response to more abnormally hot weather. However, the fact that the positive sensitivity does not disappear in high-dimensional fixed effect models (see Section 3.4), which compare investment decisions of firms within electricity markets or states that are likely subject to the same environmental regulation, and our finding that investment sensitivities are insignificant for wind and solar make it unlikely that the environmental channel plays a dominant role.

For pump storage pants, the estimated coefficient is negative and marginally significant, but its economic magnitude is small (0.11 vs 0.65 for CCGT).[20] For nuclear power plants, we find a negative and statistically significant investment-weather sensitivity. This finding is also in line with the notion that more demand variability reduces the attractiveness of very inflexible nuclear power plants. For all other production technologies, we find no statistically significant investment-weather sensitivities. Overall, the results from this test are in line with our proposed demand channel: energy utilities do not generally invest more in power plants but respond to higher demand and price variability by concentrating their investments in flexible plants.

5.2. Hot weather and electricity prices

Our proposed mechanism assumes that hot weather leads to more air conditioning and demand for electricity. Since shocks to demand for electricity are reflected immediately in its wholesale market price, a way to evaluate the importance of the channel we propose is to see if this link is present in the data. An advantage of focusing on electricity prices is the availability of high-frequency, hourly price data. Therefore, we estimate the way in which unusually hot weather affects wholesale market pricing of electricity. We collect data on hourly electricity prices directly from the exchanges and from Thomson-Reuters Eikon (see Lin, Schmid, and Weisbach, 2020, for more details). We are able to obtain hourly electricity prices for 38 different markets. Electricity prices are measured in US$ per megawatt hour (MWh) and local electricity prices are converted to US$ using daily exchange rates.

Our first test analyzes the way in which hot weather on a particular day affects the average hourly electricity price and their distribution on that day. Panel A of Table 7 presents estimated equations predicting the electricity price level. A day is classified as hot if it would belong to the hottest one percent of days in that region during the base period. In Column 1, the specification only includes market x day-of-

[20] The negative investment-weather sensitivity for pump storage plants should be interpreted with caution because the negative coefficient estimate for abnormally hot weather is mainly driven by a few exceptionally large pump storage plants. If we exclude the six pump storage plants with more than 500 MW capacity, the coefficient estimate for abnormally hot weather falls from -0.11 (t-value: -1.93) in our baseline specification to -0.012 (t-value: -0.94).

the-week fixed effects to account for different price patterns within weeks, since electricity prices tend to be lower on weekends since industrial consumption is lower. The estimates indicate that abnormally hot weather leads to higher electricity prices. The magnitude of this effect is substantial, with a price difference of about one-quarter between days that are classified as hot and "normal" days.

The results are similar for the estimates in Column 2 which include controls for gas prices, important determinants of electricity prices. In Column 3, we include market times month times year fixed effects in addition to the market times day-of-the-week fixed effects. This specification exploits variation within a specific month in a market and controls for all factors that vary at a lower frequency within market (since we measure gas prices on a monthly basis, they are dropped in this specification). Column 4 uses week instead of month fixed effects to explore changes within a specific week and market. In each specification, the coefficient estimate implies that the electricity prices is about twenty-five percent higher on hot days.

In Panel B, we analyze the intraday price distribution of the hourly electricity prices. In Columns 1 and 2 we report estimated equations predicting the standard deviation of the hourly prices on a particular day. We find that the standard deviation of electricity prices is six to seven percent higher on hot days than on normal days. For the interquartile range, which is reported in Columns 3 and 4, we find a similar pattern: on hot days, the difference between the 25% and the 75% percentile is three to six percent higher than on normal days. These results are in line with the idea that hot weather on a particular day leads to higher prices and more intra-day price variability, leading flexible power plants to be more valuable.

5.3. Hot weather and the within-year variation in electricity prices

In addition to higher intra-day price variability, the argument that hotter weather leads to greater more variable demand for electricity and consequently to utilities' investments in flexible power plants, also implies that hotter weather should cause a higher intra-year price variability between the different seasons. We next examine whether this pattern holds in the data.

Table 8 contains estimates of equations predicting the mean as well as various percentiles of the distribution of daily secondary market electricity prices throughout the year. We find that hotter weather leads to higher average electricity prices, with a one-standard deviation increase in *Abnormal Hot Weather* leading to a three-percent increase of average electricity prices. When we analyze the price distribution, we find that this effect is mainly driven by the upper tail of the price distribution. The impact of hot weather is strongest for the 90% and 95% percentile of the electricity prices. In terms of economic significance, the impact of hot weather on the 95% percentile is about twice as strong as for the average electricity price. Hot weather has no significant impact on any quantile below the median. These results indicate that seasonal variation in electricity prices increase with the incidence of hot weather, making flexible power plants more valuable for firms. Because of their low fixed cost and short start times, they can be switched on whenever the electricity price exceeds their production cost.

5.4. The direct effect of hot weather on electricity demand

Presumably the reason why electricity prices vary with the incidence of hot weather is that hot weather increases the demand for electricity. Using data on electricity usage, we test this hypothesis directly. We obtain monthly electricity generation data from the IEA Monthly Electricity Statistics for individual countries and from the EIA Electric Power Monthly for U.S. states.

We estimate equations predicting electricity demand as a function of *Abnormal Hot Weather*, using the same approach as we used to estimate the annual distribution of electricity prices in Table 8. The results, which are reported in Table 9, suggest that electricity demand follows a similar pattern to electricity prices. More hot weather increases demand, especially in the upper tail of the distribution. The strongest effects of hot weather is for the 90% and 95% percentile of demand, while the impact of hot weather on demand is not significantly different from zero for percentiles below the median. This pattern provides additional support for the demand channel, since it shows that hotter weather increases peak demand.

5.5. The impact of air conditioning

Hotter weather leads to more demand, higher and more volatile prices, and, investments in flexible power plants that can adjust output at low cost. A plausible reason for these effects is the increased use of air conditioning because of the hot weather. We next examine the role of air conditioning directly.

While air conditioning is widely used in the U.S., its prevalence is more heterogenous in Europe and Asia.[21] Two key factors affecting the use of air conditioning in a country are the country's climate and its level of development (see Lapillonne, 2019). We use variation in those two factors to approximate the prevalence in a particular electricity market. To measure the demand for air conditioning because of climatic conditions in a region, we use the number of cooling degree days during the base period. Cooling degree days measure the amount of energy that is needed for cooling and are calculated as the number of degrees that the average temperature on a day is above the reference temperature (we use 65 degrees Fahrenheit, which is most common in the U.S.). Our measure of economic development is the average gross domestic product in a region during our sample period. In addition, we use the sensitivity of daily electricity prices to hot weather in a particular region as a market-based measure for the use of air conditioning.

The results are reported in Table 10. In Panel A, we use cooling degree days as proxy for cooling demand and thus the prevalence of air conditioning. We find that investments in flexible plants do not depend on hot weather in the one-third of our sample regions that have the lowest cooling demand. For the middle and upper third of regions, hotter weather leads to more investments in flexible plants. The interaction term between cooling demand and hot days is positive and not statistically significantly different from zero, possibly because the impact of cooling demand is not linear. We find a similar pattern if we approximate economic development by GDP per capita in Panel B: there is a positive investment-weather

[21] A survey in 2015 showed that 90 percent of American households have air conditioning of some sort while the corresponding figure for India is only five percent in 2017. See https://www.bloomberg.com/news/articles/2019-07-10/why-we-always-fight-over-air-conditioning) and https://www.theverge.com/2017/9/14/16290934/india-air-conditioner-cooler-design-climate-change-cept-symphony

sensitivity in regions with medium and high levels of economic development, but not in those where GDP per capita is low.

In Panel C, we use the sensitivity of electricity prices to hot weather as a market-based measure of the air conditioning usage. We estimate market-specific regressions of daily electricity prices on a dummy variable that indicates hot days to calculate this measure, using the specification analogous to that presented in Column 4 in Panel A of Table 7. We find that the investment-weather sensitivity is statistically insignificant for the regions with the smallest reaction of electricity prices on hot days (Column 1). In regions with a medium reaction of electricity prices to hot days in Column 2, we find a positive and statistically significant coefficient estimate of the investment-weather sensitivity. This sensitivity is substantially higher with a coefficient estimate of 3.53 (vs. 0.96) in regions where electricity prices react strongly to heat (Column 3). The interaction term in Column 4 confirms this pattern, and indicates that the investment-weather sensitivity is concentrated in regions where electricity prices increase a lot on hot days. A heavy use of air conditioning appears to be the most likely explanation for this price increase.

5.2. The role of operating flexibility

Our hypothesis is that energy firms invest in flexible generation assets to increase their operating flexibility and adjust to more volatility electricity prices. An additional prediction is that a firm’s existing operating flexibility should affect its likelihood to invest in flexible power plants. Abnormally hot weather conditions and the associated changes in the demand for electricity should be especially problematic for firms with low levels of existing operating flexibility. Thus, we expect that investments in flexible generation should be larger for firms that have low levels of existing operating flexibility.

Table 11 presents estimates of equations predicting investments in flexible power plants as a function of firms’ existing flexibility. We define existing operating flexibility as a firm’s flexible production capacity scaled by the sum of flexible and inflexible capacity. In the first three columns, we split the sample into observations with low, media, and high operating flexibility. Abnormally hot weather has a strong positive impact on flexible investments for firms with low levels of operating flexibility in Column 1. For firms with median and high levels of existing operating flexibility in Columns 2 and 3, the coefficient estimates for abnormally hot weather are positive but statistically not different from zero. Using an interaction term for the full sample in Column 4 of firms confirms this result. These estimates suggest that investments in flexible assets are concentrated in firms with lower levels of existing operating flexibility.

6. Conclusion

The changing climate is potentially one of the most consequential phenomena in human history. Much attention has been focused on the way changing weather patterns affects ocean levels, the likelihood and violence of storms, and agricultural productivity. Yet, there are many other potential effects of climate change that could impact many aspects of the economy. Firms in a number of different industries will have to alter the way that they do business, sometimes in a substantial way. The ability to adjust their operations quickly to new situations and market conditions has potentially become more important. We study the effect of the frequency of extreme temperatures on one industry that is likely to be considerably affected by it, the electricity producing industry.

A major factor in the demand for electricity is the weather. Theoretically, more extreme temperatures can lead to large fluctuations in electricity demand and the wholesale price of electricity, which in turn affects the optimal production process for firms to use. Especially flexible power plants which can quickly adjust their production to changing market conditions can become more valuable in such a situation, and firms might increase their investments in those types of plants. Alternatively, climate change and extreme weather can increase uncertainty for energy firms, causing them to delay their investments.

In this paper, we consider a sample of 258 electricity producing firms operating in 45 electricity markets over the 2000-2016 period. These firms have 5,041 planned power plant projects, of which 1,605 are flexible gas, oil, or pump storage plants. We evaluate the extent to which changes in the regional frequency of abnormally hot temperatures affected our sample firms' decisions to invest in new flexible power plants. The estimates indicate that the quantity of new, flexible power plants that firms build increases in regions in which temperatures are becoming hotter. These estimates imply that a one standard deviation increase in the frequency of days with abnormally hot temperatures leads to a 15 to 25 percent relative increase in investments in flexible plants, suggesting that changes in weather have had a substantial impact on these firms' investment decisions.

This change appears to be occurring because hotter temperatures today are indicative of hotter temperatures in the future since the effect only occur in regions in which the CMIP5 models produced by climate scientists around the world suggest will be experiencing temperature increases in the future. We provide a number of additional tests that suggest that the mechanism for this increase is that hotter weather leads to more air conditioning use, which then leads to more volatile electricity demand and prices. Firms react to this higher volatility by investing in a way that improves their operating flexibility by investing in power plants that can be started and stopped quickly and at low cost.

These results are consistent with the view that climate change has affected the investment decisions of electricity producing firms. Presumably, as the earth continues to warm and weather becomes even more extreme, firms will continue to favor flexible power plants for which output can be adjusted easily. Ironically, the type of plant most responsible for the CO_2 emissions that cause climate change is the coal-fired plant. These plants are relatively inflexible, so have a relatively high cost of changing their output. Consequently, because of climate change, firms appear to be shifting away from the coal fired plants, not because of their CO_2 emissions, but because of their inflexibility. Unfortunately, the weather induced shift has not been to renewable energy, although there has been an increase in renewables for other reasons.

While the question of how utilities' make investments in new power plants is an important issue, we hope that our paper makes a larger point: changing weather conditions fundamentally change the economics of many businesses. Our results suggest that it leads energy producing companies to increase investments to enhance their operating flexibility. In addition, changing weather conditions potentially lead firms to invest more in other industries as well. However, the impact of culminate change on the way firms in different industries invest is likely to vary substantially. Future research that characterizes the way in which climate change affects different industries is likely to be fruitful.

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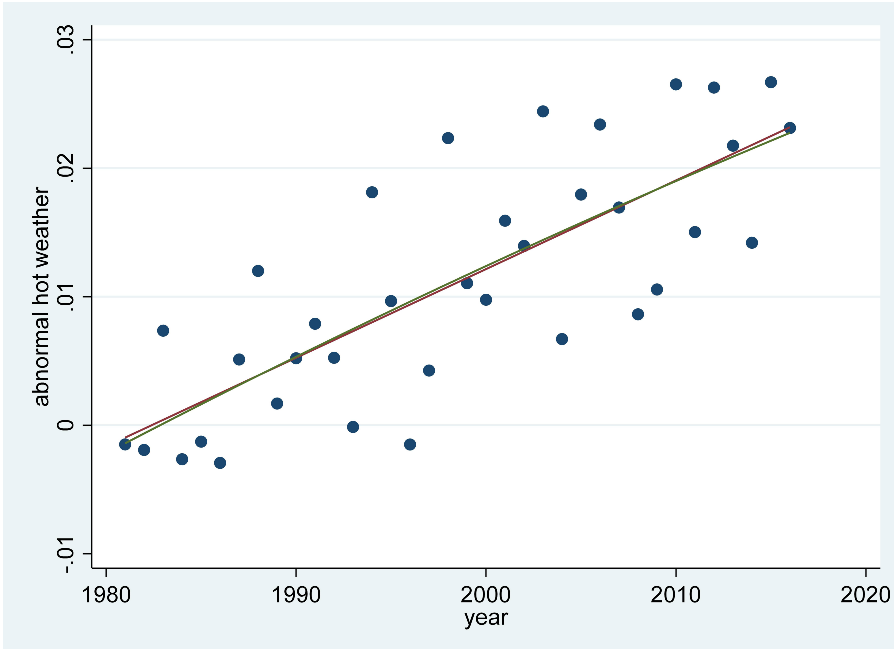

Figure 1: This figure shows the average abnormal hot weather across all electricity markets over time. A day is classified as hot if its temperature would belong to the 1% hottest days in market m during the base period 1951 to 1980. Abnormal hot weather is the annual fraction of hot days in electricity market m minus 1% (the fraction of hot days during the base period). Linear and quadratic fits are shown in red and green, respectively.

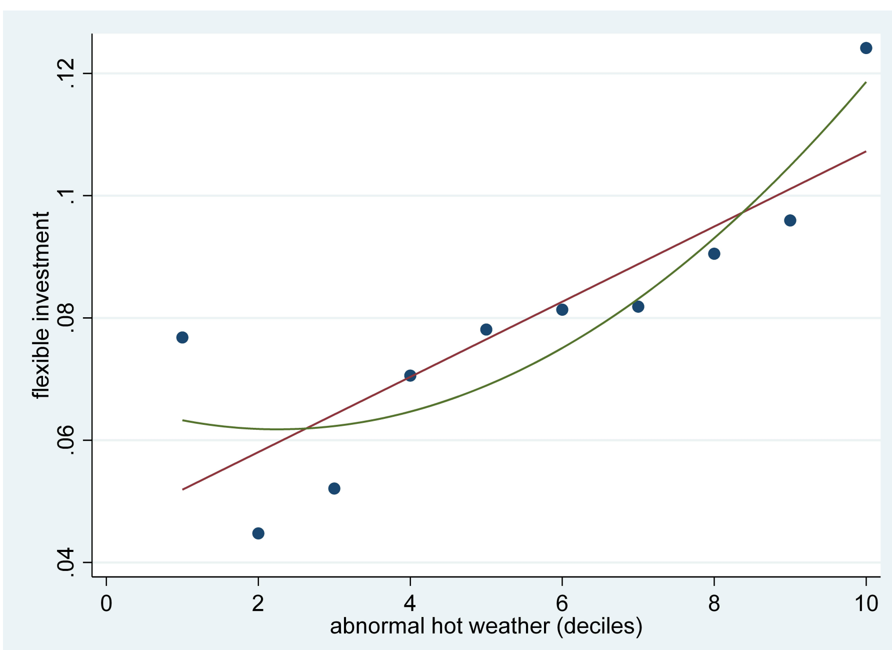

Figure 2: This figure shows average flexible investments for deciles of abnormal hot weather. Flexible investment is defined as planned flexible power plant construction projects (in megawatt, MW) of firm i in the electricity market region m and year t, scaled by the capacity of existing power plants (in MW) of firm i in market m and year t. Gas, oil, and pump storage power plants are classified as flexible plants. Linear and quadratic fits are shown in red and green, respectively.

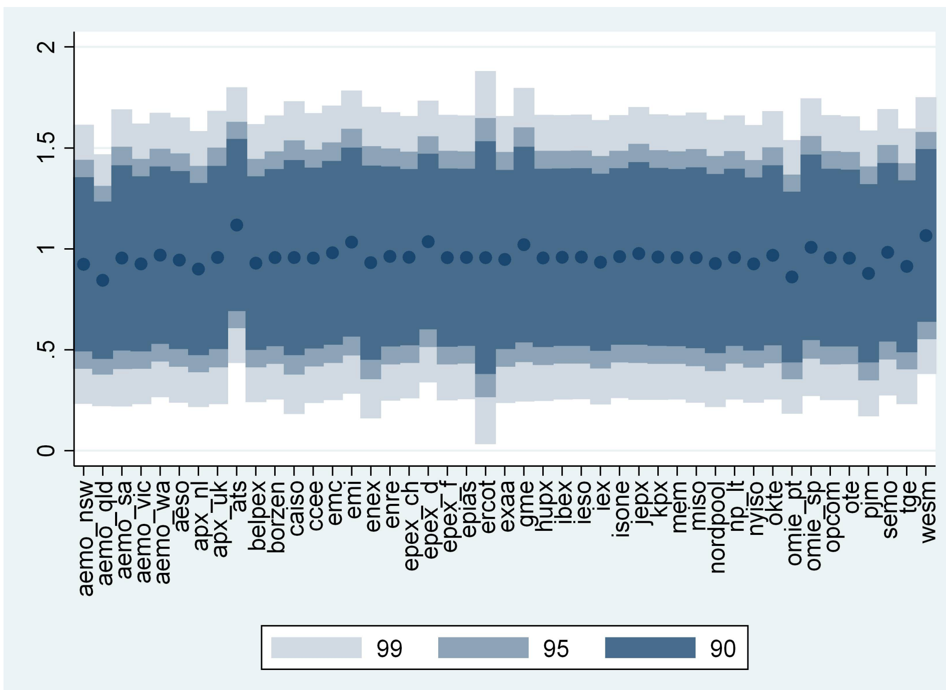

Figure 3: Coefficient estimates for our base model in Column 4 of Panel A, Table 3, when we subsequently exclude single markets.

Table 1: Descriptive statistics: planned power plant projects

Technology	total number	total GW	capacity (MW) average	capacity (MW) median
Flexible	**1,598**	**423**	**182**	**156**
Gas	1,394	390	280	231
simple cycle combustion turbine	614	91	148	152
combined cycle gas turbine	601	291	484	420
gas-fired reciprocating engine	115	1	11	10
unspecified	64	8	159	117
Pump storage	117	29	246	225
Oil	87	4	47	10
Inflexible	**673**	**485**	**772**	**774**
Coal	580	361	622	660
bituminous	120	77	642	660
subbituminous	25	16	652	600
lignite	53	33	616	564
unspecified	382	235	615	660
Nuclear	93	124	1,335	1,385
Renewable	**2,537**	**279**	**74**	**30**
Wind	1,118	128	115	50
Hydro	997	129	130	40
Solar	248	13	51	15
Biogas	52	1	21	9.65
Biomass	63	5	78	25
Geothermal	59	3	51	40
Others	**194**	**33**	**242**	**238**
Total	**5,002**	**1,221**	**244**	**110**

This table presents descriptive statistics for the planned investment projects of the sample firms. Reported are the total number of power plant projects, the total capacity of planned plants in gigawatt (GW), and the average and median capacity of planned plants in megawatt (MW). We count each unit of a power plant separately since different units of a plant can be constructed at different time and use different production technologies.

Table 2: Descriptive statistics: firm and market-level

Panel A: Firm-market-year sample						
Variable	**Obs**	**Mean**	**p25**	**p50**	**p75**	**SD**
Flexible investment$_t^{i,m}$	4,956	0.078	0.000	0.000	0.028	0.203
Abnormal hot weather$_t^m$	4,956	0.016	-0.002	0.008	0.023	0.027
Abnormal hot weather$_{t-1,t-4}^m$	4,956	0.015	0.001	0.007	0.022	0.021
Cc prediction^m	4,928	12.907	10.283	14.420	16.000	4.684
Log(cc prediction)^m	4,928	2.458	2.330	2.669	2.773	0.507
Cc uncertainty^m	4,928	0.484	0.388	0.468	0.516	0.189
log(cc uncertainty^m)	4,928	-0.782	-0.946	-0.759	-0.662	0.320
Market share$_t^{i,m}$	4,857	0.061	0.006	0.023	0.067	0.115
Operating flex$_{t-1}^i$	4,206	0.566	0.319	0.594	0.790	0.307
Assets (US$ bn)$_{t-1}^i$	4,358	35.594	5.320	24.784	55.100	34.063
Log(assets)$_{t-1}^i$	4,358	16.571	15.487	17.026	17.825	1.631
Leverage$_{t-1}^i$	4,358	0.532	0.431	0.545	0.656	0.188
Tobin's Q$_{t-1}^i$	4,100	1.168	0.995	1.106	1.268	0.402
Profitability$_{t-1}^i$	4,302	0.065	0.047	0.064	0.082	0.039
Cash$_{t-1}^i$	4,356	0.072	0.023	0.054	0.101	0.069
Log(GDP per capita)$_{t-1}^m$	4,867	10.280	10.028	10.715	10.807	0.870
Inflation$_{t-1}^m$	4,730	2.841	1.473	2.438	3.383	2.624
Log(GDP per capita$_{t-1}^{HQ}$)	4,853	10.399	10.423	10.695	10.790	0.750
Inflation$_{t-1}^{HQ}$	4,775	2.505	1.380	2.069	3.157	2.473
Panel B: Market-year sample						
Abnormal hot weather$_t^m$	618	0.016	-0.002	0.009	0.026	0.026
El demand$_t^m$ [TWh]	493	22.766	7.294	18.793	31.707	19.449
El price$_t^m$ [US$/MWh]	498	52.821	35.140	48.114	64.058	26.601
Gas price$_t^m$ [US$/MWh]	410	31.364	19.190	29.346	42.228	14.654
log(GDP per capita$_t^m$)	618	10.329	10.000	10.704	10.810	0.769
Inflation$_t^m$	585	2.410	1.262	2.184	3.226	2.152
Panel C: Market-day sample						
Hot day$_d^m$ [dummy]	181,552	0.025	0.000	0.000	0.000	0.156
El price$_h^m$ [US$/MWh]	182,014	55.240	29.492	44.956	65.404	61.941
SD(El Price$_h^m$)	181,891	0.299	0.160	0.239	0.350	1.960
IQR(El Price$_h^m$)	181,892	0.373	0.197	0.323	0.490	2.503
Gas price$_{m/q}^m$ [US$/MWh]	121,090	31.667	19.473	30.762	42.757	14.507

This table presents descriptive statistics for the firm-market-year sample (Panel A), the market-year sample (Panel B), and the market-day sample (Panel C). Reported are the number of observations (N), mean value, p25, p50, p75, and standard deviation (SD). A detailed description of all variables can be found in Appendix A.

Table 3: Hot weather and investments in flexible power plants

Column	1	2	3	4
Abnormal hot weather$^{m}_{t-1,t-4}$	**0.99***** **(3.16)**	**1.07***** **(2.92)**	**1.31***** **(3.60)**	**0.96***** **(3.67)**
Year FE	no	yes	yes	yes
Firm FE	no	no	yes	yes
Firm x market FE	no	no	no	yes
Observations	4,956	4,956	4,936	4,898
Adj. R^2	0.010	0.014	0.21	0.54

The dependent variable is FLEXIBLE INVESTMENT$^{i,m}_{t}$, which is defined as planned flexible power plant construction projects (in megawatt, MW) of firm i in the electricity market region m and year t, scaled by the capacity of existing power plants (in MW) of firm i in market m and year t. Gas, oil, and pump storage power plants are classified as flexible plants. ABNORMAL HOT WEATHER$^{m}_{t-1,t-4}$ is the annual fraction of hot days over the three-year period from $t-1$ to $t-4$ in electricity market m minus 1% (the fraction of hot days during the base period). A day is classified as hot if its temperature would belong to the 1% hottest days in market m during the base period 1951 to 1980. T-statistics based on robust standard errors clustered by electricity market regions and firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Table 4: High-dimensional fixed effects models

Panel A: Firm-year and country-year fixed effects				
Column	1	2	3	4
Abnormal hot weather$^{m}_{t-1,t-4}$	**1.39***** **(2.83)**	**1.51***** **(3.64)**	**1.98***** **(3.21)**	**2.18***** **(3.92)**
Firm x year FE	yes	yes	no	yes
Firm x market FE	no	yes	yes	yes
Country x year FE	no	no	yes	yes
Observations	3,289	3,243	4,844	3,132
Adj. R^2	0.097	0.59	0.54	0.59

Panel B: Market or state-year fixed effects (U.S. only)				
Column	1	2	3	4
Abnormal hot weather$^{c}_{t-1,t-4}$	**0.60***** **(3.17)**	**0.61***** **(3.19)**	**0.55**** **(2.62)**	**0.52**** **(2.38)**
Firm x year FE	no	yes	no	yes
Market x year FE	yes	yes	n/a	n/a
Firm x market FE	yes	yes	n/a	n/a
State x year FE	no	no	yes	yes
Firm x state FE	no	no	yes	yes
Observations	4,243	4,038	4,202	3,995
Adj. R^2	0.12	0.099	0.14	0.11

In Panel A, the dependent variable is FLEXIBLE INVESTMENT$^{i,m}_{t}$, which is defined as planned flexible power plant construction projects (in megawatt, MW) of firm i in the electricity market region m and year t, scaled by the capacity of existing power plants (in MW) of firm i in market m and year t. Gas, oil, and pump storage power plants are classified as flexible plants. ABNORMAL HOT WEATHER$^{m}_{t-1,t-4}$ is the annual fraction of hot days over the three-year period from $t-1$ to $t-4$ in electricity market m minus 1% (the fraction of hot days during the base period). A day is classified as hot if its temperature would belong to the 1% hottest days in market m during the base period 1951 to 1980. T-statistics based on robust standard errors clustered by electricity market regions and firms are presented in parentheses.
Panel B presents a county-year level analysis for U.S. markets. These markets use nodal pricing, which leads to differences in electricity prices within market regions. The dependent variable is FLEXIBLE INVESTMENT$^{i,c}_{t}$, which is defined as planned flexible power plant construction projects (in megawatt, MW) of firm i in county c and year t, scaled by the capacity of existing power plants (in MW) of firm i in county c and year t. Gas, oil, and pump storage power plants are classified as flexible plants. ABNORMAL HOT WEATHER$^{c}_{t-1,t-4}$ is the fraction of hot days in county c over the three-year period from $t-1$ to $t-4$. A day is classified as extreme if its temperature would belong to the 1% hottest days in county c during the base period 1951 to 1980. T-statistics based on robust standard errors clustered by U.S. states and firms are presented in parentheses.
***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Table 5: Climate change predictions and the investment-weather sensitivity

Panel A: Predicted change of summer days (mean across CMIP5 models)					
Column	1	2	3	4	5
Sample	low	medium	high	all	$\geq$ 2006
Abnormal hot weather$^{m}_{t-1,t-4}$	**0.46**	**1.01*****	**1.53*****	1.22***	1.09***
	(0.91)	**(3.19)**	**(3.71)**	(4.59)	(4.32)
AHW$^{m}_{t-1,t-4}$ x log(cc prediction^{m})				**0.90****	**1.03*****
				(2.52)	**(2.85)**
Year FE	yes	yes	yes	yes	yes
Firm x market FE	yes	yes	yes	yes	yes
Observations	1,841	1,464	1,565	4,870	4,005
Adj. R^2	0.64	0.42	0.57	0.54	0.63
Panel B: Prediction uncertainty (SD across CMIP5 models)					
Column	1	2	3	4	5
Sample	low	medium	high	all	$\geq$ 2006
Abnormal hot weather$^{m}_{t-1,t-4}$	**1.74*****	**0.86*****	**0.56**	1.06***	0.95***
	(3.54)	**(4.19)**	**(0.97)**	(4.17)	(3.94)
AHW$^{m}_{t-1,t-4}$ x log(cc uncertainty^{m})				**-1.09**	**-1.51****
				(-1.40)	**(-2.05)**
Year FE	yes	yes	yes	yes	yes
Firm x market FE	yes	yes	yes	yes	yes
Observations	1,812	1,472	1,586	4,870	4,005
Adj. R^2	0.49	0.64	0.44	0.54	0.63

The dependent variable is FLEXIBLE INVESTMENT$^{i,m}_{t}$, which is defined as planned flexible power plant construction projects (in megawatt, MW) of firm i in the electricity market region m and year t, scaled by the capacity of existing power plants (in MW) of firm i in market m and year t. Gas, oil, and pump storage power plants are classified as flexible plants. ABNORMAL HOT WEATHER$^{m}_{t-1,t-4}$ is the annual fraction of hot days over the three-year period from $t-1$ to $t-4$ in electricity market m minus 1% (the fraction of hot days during the base period). A day is classified as hot if its temperature would belong to the 1% hottest days in market m during the base period 1951 to 1980.
CC prediction is the predicted change in summer days in electricity market region m between the base period 1986 to 2005 and forecast period 2020 to 2039. We use the RCP4.5 scenario and average the predictions across all Coupled Model Intercomparison Project Phase (CMIP) 5 models. Summer days are defined as days with a maximum temperature above 25 degrees Celsius; due to data constraints, we apply a threshold of 30 degrees Celsius for Australian markets. CC uncertainty is the standard deviation of the predicted change in summer days across all available CMIP5 models. All interacted variables are centered. T-statistics based on robust standard errors clustered by electricity market regions and firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Table 6: Technology-specific investment-weather sensitivities

Panel A: Flexible plants					
Column	1	2	3	4	5
Technology	gas (CCGT)	gas (SCCT)	gas (GFRE)	oil	hydro (pump)
AHW$^{m}_{t-1,t-4}$	**0.65****	**0.37****	**-0.0028**	**-0.0016**	**-0.11***
	(2.52)	**(2.16)**	**(-0.85)**	**(-0.13)**	**(-1.93)**
Year FE	yes	yes	yes	yes	yes
Firm x market FE	yes	yes	yes	yes	yes
Observations	4,898	4,898	4,898	4,898	4,898
Adj. R^2	0.51	0.40	0.075	0.10	0.85
Panel B: Inflexible plants					
Column	1	2	3	4	5
Technology	coal (bituminous)	coal (subbituminous)	coal (lignite)	coal (unspecified)	nuclear (uranium)
AHW$^{m}_{t-1,t-4}$	**-0.041**	**-0.12**	**-0.083**	**0.19**	**-0.23***
	(-0.23)	**(-1.11)**	**(-1.35)**	**(1.13)**	**(-1.99)**
Year FE	yes	yes	yes	yes	yes
Firm x market FE	yes	yes	yes	yes	yes
Observations	4,898	4,898	4,898	4,898	4,898
Adj. R^2	0.48	0.86	0.67	0.79	0.30
Panel C: Renewable plants					
Column	1	2	3	4	5
Technology	hydro (conv)	wind	solar	biogas/mass	geothermal
AHW$^{m}_{t-1,t-4}$	**0.071**	**0.016**	**0.082**	**0.023**	**0.0057**
	(0.44)	**(0.080)**	**(0.36)**	**(1.18)**	**(0.10)**
Year FE	yes	yes	yes	yes	yes
Firm x market FE	yes	yes	yes	yes	yes
Observations	4,898	4,898	4,898	4,898	4,898
Adj. R^2	0.81	0.72	0.56	0.31	0.66

AHW stands for abnormal hot weather. The dependent variable is the investment of firm i in power plants that use technology f. It is calculated as planned power plant construction projects (in megawatt, MW) that use technology f of firm i in the electricity market region m and year t, scaled by the capacity of existing power plants (in MW) of firm i in market m and year t. CCGT stands for combined cycle gas turbine, SCCT for simple cycle combustion turbine, and GFRE for gas-fired reciprocating engine. Abnormal hot weather$^{m}_{t-1,t-4}$ is the annual fraction of hot days over the three-year period from $t-1$ to $t-4$ in electricity market m minus 1% (the fraction of hot days during the base period). A day is classified as hot if its temperature would belong to the 1% hottest days in market m during the base period 1951 to 1980. T-statistics based on robust standard errors clustered by electricity market regions and firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Table 7: Hot weather and daily electricity prices (market-day level)

Panel A: Daily electricity price level				
Column	1	2	3	4
	$Log(ElP_h^m)$			
Hot day$_d^m$	**0.22***** **(3.84)**	**0.19***** **(3.01)**	**0.24***** **(4.29)**	**0.20***** **(3.84)**
Gas price$^m_{\mathrm{m/q}}$		0.023*** (6.92)	n/a	n/a
Market x day FE	yes	yes	yes	yes
Market x month x year FE	no	no	yes	n/a
Market x week x year FE	no	no	no	yes
Observations	169,746	109,151	169,744	169,656
Adj. R^2	0.32	0.33	0.81	0.86

Panel B: Intraday distribution of hourly electricity prices				
Column	1	2	3	4
	$Log[SD(ElP_h^m)]$		$Log[IQR(ElP_h^m)]$	
Hot day$_d^m$	**0.072***** **(3.08)**	**0.061***** **(2.93)**	**0.062***** **(3.49)**	**0.028***** **(3.25)**
Market x day FE	yes	yes	yes	yes
Market x week x year FE	no	yes	no	yes
Observations	169,608	169,518	169,623	169,532
Adj. R^2	0.18	0.52	0.20	0.57

This table uses the market-day sample to analyze how hot weather affects the wholesale market prices of electricity (in US$ per MWh). In Panel A, the dependent variable is logarithm of ElP$_d^m$, that is the average electricity price in market m on day d over all 24 hours. The dependent variable in Columns 1 and 2 of Panel B are the logarithms of the standard deviation of hourly electricity prices in market m on day d and the interquartile range of hourly electricity prices in market m on day d. Hourly electricity price data comes directly from the power exchange or ThomsonReuters Eikon. HOT DAY$_d^m$ is a dummy variable that equals one if day d is classified as hot and zero otherwise. A day is classified as hot if it would belong to the 1% hottest days in market m during the base period 1951 to 1980.

T-statistics based on robust standard errors clustered by electricity markets are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Table 8: Hot weather and the annual distribution of daily electricity prices (market-year level)

Column	1	2	3	4	5	6	7	8
Dependent (log)	mean	p5	p10	p25	p50	p75	p90	p95
AHW_t^m	**1.09****	**0.85**	**0.61**	**0.46**	**0.98****	**1.24*****	**1.49*****	**1.96*****
	(2.62)	**(0.66)**	**(0.77)**	**(0.81)**	**(2.22)**	**(3.42)**	**(3.89)**	**(2.82)**
Gas price$_t^m$	0.017***	0.017**	0.019***	0.021***	0.021***	0.020***	0.015***	0.012**
	(5.76)	(2.74)	(4.17)	(5.84)	(6.87)	(7.32)	(4.25)	(2.64)
Log(GDP per c.$_t^m$)	0.45	2.61**	1.26*	0.44	0.15	0.29	0.39	0.55
	(0.78)	(2.45)	(1.90)	(0.82)	(0.28)	(0.54)	(0.66)	(0.86)
Inflation$_t^m$	-0.0085	-0.062	-0.032	-0.012	-0.012	-0.010	-0.0052	-0.00046
	(-0.54)	(-1.67)	(-1.44)	(-0.76)	(-0.77)	(-0.62)	(-0.27)	(-0.025)
Year-FE	yes	yes	yes	yes	yes	yes	yes	yes
Region-FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	354	354	354	354	354	354	354	354
Adj. R^2	0.78	0.61	0.72	0.80	0.80	0.77	0.68	0.63

AHW stands for abnormal hot weather. This tables uses the market-year sample to analyze how hot weather affects the annual distribution of daily electricity prices (in US$ per MWh). Hourly electricity price data comes directly from the power exchange or ThomsonReuters Eikon. Median, mean, min, max, and the quantiles are the respective statistics of the price in electricity market m and year t. All dependent variables are in log terms. ABNORMAL HOT WEATHER$_{t-1,t-4}^m$ is the annual fraction of hot days over the three-year period from $t-1$ to $t-4$ in electricity market m minus 1% (the fraction of hot days during the base period). A day is classified as hot if its temperature would belong to the 1% hottest days in market m during the base period 1951 to 1980.
T-statistics based on robust standard errors clustered by electricity markets are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Table 9: Hot weather and the distribution of monthly electricity demand (market-year level)

Column	1	2	3	4	5	6	7	8
Dependent (log)	mean	p5	p10	p25	p50	p75	p90	p95
AHW$_t^m$	**0.32***	**0.14**	**0.12**	**0.22**	**0.33****	**0.31****	**0.38****	**0.49*****
	(1.98)	**(0.47)**	**(0.40)**	**(0.86)**	**(2.16)**	**(2.25)**	**(2.54)**	**(2.87)**
Log(GDP per c.$_t^m$)	0.26***	0.30***	0.32***	0.36***	0.28***	0.16*	0.19*	0.20
	(3.08)	(3.52)	(4.24)	(5.24)	(3.11)	(1.70)	(1.71)	(1.24)
Inflation$_t^m$	0.0060	0.0047	0.0065	0.0037	0.0056	0.0071*	0.0093**	0.011**
	(1.47)	(0.83)	(1.12)	(0.73)	(1.44)	(1.77)	(2.08)	(2.22)
Year-FE	yes	yes	yes	yes	yes	yes	yes	yes
Region-FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	493	493	493	493	493	493	493	493
Adj. R^2	0.069	0.037	0.047	0.068	0.071	0.042	0.059	0.064

AHW stands for abnormal hot weather. This tables uses the market-year sample to analyze how hot weather affects the annual distribution of monthly electricity demand (in GWh). Monthly electricity generation data comes from the IEA's Monthly Electricity Statistics for individual countries and from EIA' Electric Power Monthly for U.S. states. We aggregate country and state-level data to electricity market regions and assume that electricity generation equals demand and ignore imports/exports. Median, mean, min, max, and the quantiles are the respective statistics of the monthly electricity demand in electricity market m and year t. All dependent variables are in log terms. Abnormal hot weather$_{t-1,t-4}^m$ is the annual fraction of hot days over the three-year period from $t-1$ to $t-4$ in electricity market m minus 1% (the fraction of hot days during the base period). A day is classified as hot if its temperature would belong to the 1% hottest days in market m during the base period 1951 to 1980.
T-statistics based on robust standard errors clustered by electricity markets are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Table 10: Variation in air conditioning use across regions

Panel A: Cooling demand				
Column	1	2	3	4
Sample	low	medium	high	all
Abnormal hot weather$^{m}_{t-1,t-4}$	**0.60**	**1.21*****	**1.08****	1.02***
	(0.92)	**(3.20)**	**(2.66)**	(4.21)
AHW$^{m}_{t-1,t-4}$ x log(CDD$^{m}_{base}$)				**0.093**
				(1.17)
Firm x market FE	yes	yes	yes	yes
Firm x year FE	yes	yes	yes	yes
Country x year FE	yes	yes	yes	yes
Observations	1,745	1,761	1,392	4,898
Adj. R^2	0.56	0.49	0.62	0.54
Panel B: Gross domestic product per capita				
Column	1	2	3	4
Sample	low	medium	high	all
Abnormal hot weather$^{m}_{t-1,t-4}$	**0.38**	**1.29****	**1.65*****	1.07***
	(1.06)	**(2.38)**	**(3.23)**	(4.60)
AHW$^{m}_{t-1,t-4}$ x log(GDP per c.$^{m}_{avg}$)				**0.47**
				(1.35)
Firm x market FE	yes	yes	yes	yes
Firm x year FE	yes	yes	yes	yes
Country x year FE	yes	yes	yes	yes
Observations	1,707	1,570	1,533	4,810
Adj. R^2	0.58	0.46	0.55	0.54
Panel C: Sensitivity of daily electricity prices to heat				
Column	1	2	3	4
Sample	low	medium	high	all
Abnormal hot weather$^{m}_{t-1,t-4}$	**0.45**	**0.96****	**3.53****	1.48***
	(1.66)	**(2.61)**	**(2.98)**	(5.58)
AHW$^{m}_{t-1,t-4}$ x ela(ElP/Heat)^{m}				**4.85*****
				(3.07)
Firm x market FE	yes	yes	yes	yes
Firm x year FE	yes	yes	yes	yes
Country x year FE	yes	yes	yes	yes
Observations	1,480	1,545	1,355	4,380
Adj. R^2	0.53	0.62	0.40	0.51

continued on next page

Table 10 continued

The dependent variable is FLEXIBLE INVESTMENT$_t^{i,m}$, which is defined as planned flexible power plant construction projects (in megawatt, MW) of firm i in the electricity market region m and year t, scaled by the capacity of existing power plants (in MW) of firm i in market m and year t. Gas, oil, and pump storage power plants are classified as flexible plants. CDD$^m_{base}$ is the average yearly number of cooling degree days in market m during the base period 1951 to 1980. CDD$^m_{avg}$ is the average GDP in market m during our sample period. Cooling degree days are calcu- lated as the difference between the daily average temperature and 65F (18.3 degree Celsius); they are zero if the daily average temperature is below 65F. ElP/Heat^m is the sensitivity of daily electricity prices to hot weather conditions in market m based on market-specific regressions of daily electricity prices on a dummy variable that indicates hot days (see Column 4 in Panel A of Table 7). ABNORMAL HOT WEATHER$^m_{t-1,t-4}$ is the annual fraction of hot days over the three-year period from $t-1$ to $t-4$ in electricity market m minus 1% (the fraction of hot days during the base period). A day is classified as hot if its temperature would belong to the 1% hottest days in market m during the base period 1951 to 1980. T-statistics based on robust standard errors clustered by electricity market regions and firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Table 11: The role of operating flexibility

Column	1	2	3	4
Sample	low	medium	high	all
Abnormal hot weather$^{m}_{t-1,t-4}$	**1.22*** **	**0.73**	**0.48**	2.33***
	(2.92)	**(1.48)**	**(1.12)**	(3.20)
Operating flex$^{i}_{t-1}$				0.079
				(1.45)
AHW$^{m}_{t-1,t-4}$ x OpFlex$^{i}_{t-1}$				**-2.23** **
				(-2.28)
Firm x market FE	yes	yes	yes	yes
Firm x year FE	yes	yes	yes	yes
Country x year FE	yes	yes	yes	yes
Observations	1,574	1,571	1,565	4,783
Adj. R^2	0.55	0.67	0.55	0.54

The dependent variable is FLEXIBLE INVESTMENT$^{i,m}_{t}$, which is defined as planned flexible power plant construction projects (in megawatt, MW) of firm i in the electricity market region m and year t, scaled by the capacity of existing power plants (in MW) of firm i in market m and year t. Gas, oil, and pump storage power plants are classified as flexible plants. Operating flexibility is the ratio of flexible production capacity to flexible plus inflexible production capacity of firm i in year $t-1$. Column 1 shows the subsample of firms with low operating flexibility. Column 2 and 3 show the subsamples of medium and high operating flexibility firms. ABNORMAL HOT WEATHER$^{m}_{t-1,t-4}$ is the annual fraction of hot days over the three-year period from $t-1$ to $t-4$ in electricity market m minus 1% (the fraction of hot days during the base period). A day is classified as hot if its temperature would belong to the 1% hottest days in market m during the base period 1951 to 1980. T-statistics based on robust standard errors clustered by electricity market regions and firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Appendix

Appendix A: Definition of variables

Variable	Description
Investment variables	
Flexible investment$_t^{i,m}$	Planned flexible power plant construction projects (in megawatt, MW) of firm i in region j and year t, scaled by the capacity of existing power plants (in MW) of the same firm i in the same region j and year t. The variable is set to one if planned flexible investments exceeds total installed capacity. Gas, oil, and pump storage plants are classified as flexible plants. Source: Own calculations based on Platts WEPP data.
Flexible investment$_t^{i,c}$	The construction follows FLEXIBLE INVESTMENT$_t^{i,m}$, but we aggregate on the county-level instead of the electricity market level (U.S. only).
Weather and climate variables	
Hot day$_d^m$	Dummy variable that equals one if the temperature of day d in market m would belong to the 1% hottest days in market m during the base period 1951 to 1980. Source: Own calculations based on GHCN data.
Abnormal hot weather$_t^m$	Fraction of hot days in year t and electricity market m minus 1% (the fraction of hot days during the base period).
Days$\geq XC_t^m$	Annual number of days with a maximum temperature of $\geq X$ degrees Celsius in year t and market m.
CDD$_t^m$	Cooling degree days in year t and market m. Cooling degree days are calculated as the difference between the daily average temperature and 65F (18.3 degree Celsius); they are zero if the daily average temperature is below 65F.
CC prediction^m	Predicted change in summer days in electricity market region m between the base period 1986 to 2005 and forecast period 2020 to 2039 based on downscaled global climate models. We use the RCP4.5 scenario and average predictions across all Coupled Model Intercomparison Project Phase (CMIP) 5 models. Summer days are defined as days with a maximum temperature above 25 degrees Celsius; due to data constraints, we apply a threshold of 30 degrees Celsius for Australian markets. We use climate change data for the largest city of an electricity market in the U.S., Canada, and Australia. For all other markets, we obtain country-level climate change data from the Climate Change Knowledge Portal of the World Bank. We use Multivariate Adaptive Constructed Analogs (MACA) datasets for U.S. markets, the Climate Atlas of Canada for Canadian markets, and the Climate Change in Australia Project for Australian markets.[*]
CC uncertainty^m	Standard deviation of the predicted changes in summer days in electricity market region m between the base period 1986 to 2005 and forecast period 2020 to 2039 across all available CMIP5 models, scaled by the average predicted change in summer days in electricity market region m.

[*]See https://climateknowledgeportal.worldbank.org/ for World Bank data, https://climate.northwestknowledge.net/MACA/ for U.S. data, https://climateatlas.ca/ for Canadian data, and https://www.climatechangeinaustralia.gov.au/ for Australian data.

Definition of Variables - continued

Variable	Description
Other variables	
Electricity demand^m_m	Electricity demand in market m for month m in GWh. Monthly electricity generation data comes from the IEA's Monthly Electricity Statistics for individual countries and from EIA' Electric Power Monthly for U.S. states. We aggregate country and state-level data to electricity market regions and assume that electricity generation equals demand and ignore imports/exports. The mean and the quantiles are the respective statistics of the monthly electricity demand in electricity market m and year t.
Electricity price^m_h	Hourly wholesale market price of electricity in US$ per MWh. For most markets, the price data is directly obtained from the power exchange. If we cannot obtain the data directly from the exchange, we use price data from ThomsonReuters Eikon. The average daily electricity price ElP^m_d is calculated as the mean across all 24 hourly prices on day d in market m. SD(ElP^m_h) and SD(ElP^m_h) are calculated as the standard deviation or interquartile range of all 24 hourly prices on day d in market m. The annual mean and quantiles are the respective statistics of the daily electricity prices in electricity market m and year t.
Gas price$^m_{m/q}$	Price of natural gas in US$ per MWh in month m (for U.S. markets) or quarter q (for non-U.S. markets). The annual mean is the average of all monthly/quarterly gas prices in electricity market m and year t. Source: EIA for U.S. states and IEA for all other countries.
Spark spread^m_t	Difference between the electricity price and the cost of producing electricity using natural gas. Calculated as the median electricity price in US$ per MWh minus gas price in US$ per MWh scaled by an efficiency factor of 0.5.
EPSI^m_t	Environmental policy stringency index for the energy sector as published by the OECD.
CCPI$^m_{2019}$	Climate policy rating of the Climate Change Performance Index in 2019.
Market share^i_t	Generation capacity of of firm i in region j and year t, scaled by the total installed production capacity in region j and year t. Source: Own calculations based on Platts WEPP data.
Operating flexibility^i_t	Flexible production capacity scaled by the sum of flexible and inflexible production capacity. Source: Own calculations based on Platts WEPP data.
Assets^i_t	Total assets [wc02999] in US$. Source: Worldscope
Profitability^i_t	Earnings before interest and taxes [wc18198] scaled by total assets.
Tobin's Q^i_t	Market capitalization of equity [wc08001] plus total liabilities [wc03351] scaled by the sum of total liabilities plus book value of equity [wc03501].
Leverage^i_t	Total debt [wc03255] scaled by the sum of total debt plus book value of equity [wc03501]).
Cash^i_t	Cash and short term investments [wc02001] scaled by total assets.
GDP per capita^m_t	GDP per capita (in 2010 US$) in electricity market m and year t. Source: Worldbank.
Inflation^m_t	Yearly inflation rate in electricity market m and year t. Source: Worldbank.
GDP per capita$^{HQ}_t$	GDP per capita (in 2010 US$) in the firm's headquarter country in year t. Source: Worldbank.
Inflation$^{HQ}_t$	Inflation rate in the firm's headquarter country in year t. Source: Worldbank.

Appendix B: Control variables, market power, regulation, and gas prices

Panel A: Control variables				
Column	1	2	3	4
Abnormal hot weather$^{m}_{t-1,t-4}$	**1.26***	**0.85***	**0.95***	**0.95***
	(4.16)	**(3.05)**	**(3.53)**	**(2.84)**
Log(assets)$^{i}_{t-1}$	0.035*			0.032
	(1.69)			(1.54)
Leverage$^{i}_{t-1}$	-0.057			-0.073
	(-1.01)			(-1.16)
Tobin's Q$^{i}_{t-1}$	0.057**			0.055**
	(2.41)			(2.35)
Profitability$^{i}_{t-1}$	0.11			0.12
	(1.10)			(1.19)
Cash$^{i}_{t-1}$	0.096			0.097
	(1.18)			(1.12)
Log(GDP per capita$^{m}_{t-1}$)		0.28*		0.54***
		(1.76)		(4.02)
Inflation$^{m}_{t-1}$		0.0013		-0.00036
		(0.88)		(-0.069)
Log(GDP per capita$^{HQ}_{t-1}$)			0.044	-0.26
			(0.29)	(-1.58)
Inflation$^{HQ}_{t-1}$			0.0017	0.0019
			(0.63)	(0.33)
Year FE	yes	yes	yes	yes
Firm x market FE	yes	yes	yes	yes
Observations	3,995	4,673	4,718	3,750
Adj. R^2	0.57	0.54	0.55	0.58

Panel B: Market power of firms				
Column	1	2	3	4
Market share (capacity)	< 20%	< 10%	< 5%	all
Abnormal hot weather$^{m}_{t-1,t-4}$	**0.95***	**0.88***	**1.17***	**1.08***
	(2.89)	**(2.71)**	**(2.98)**	**(3.60)**
Market share (capacity)$^{i,m}_{t}$				-0.41
				(-1.37)
AHW$^{m}_{t-1,t-4}$ x market share$^{i,m}_{t}$				-2.29
				(-1.37)
Year FE	yes	yes	yes	yes
Firm x market FE	yes	yes	yes	yes
Observations	4,468	4,016	3,252	4,800
Adj. R^2	0.54	0.57	0.60	0.54

continued on next page

Table Appendix B continued

Panel C: Gas prices, spark spreads, and environmental regulations				
Column	1	2	3	4
Abnormal hot weather$_{t-1,t-4}^{m}$	**0.80*** **	**0.73** **	**1.33*** **	**1.10*** **
	(4.30)	**(2.15)**	**(2.97)**	**(3.94)**
Gas price$_{t-1,t-4}^{m}$	-0.00082			
	(-1.02)			
Spark spread$_{t-1,t-4}^{m}$		0.00068**		
		(2.35)		
EPSI$_{t-1,t-4}^{m}$			0.0019	
			(0.12)	
AHW$_{t-1,t-4}^{m}$ x EPSI$_{t-1,t-4}^{m}$			-0.86	
			(-1.38)	
AHW$_{t-1,t-4}^{m}$ x CCPI$_{2019}^{m}$				0.0049
				(0.47)
Year FE	yes	yes	yes	yes
Firm x market FE	yes	yes	yes	yes
Observations	3,202	2,462	3,634	4,454
Adj. R^2	0.60	0.60	0.58	0.53

The dependent variable is FLEXIBLE INVESTMENT$_{t}^{i,m}$, which is defined as planned flexible power plant construction projects (in megawatt, MW) of firm i in the electricity market region m and year t, scaled by the capacity of existing power plants (in MW) of firm i in market m and year t. Gas, oil, and pump storage power plants are classified as flexible plants. ABNORMAL HOT WEATHER$_{t-1,t-4}^{m}$ is the annual fraction of hot days over the three-year period from $t-1$ to $t-4$ in electricity market m minus 1% (the fraction of hot days during the base period). A day is classified as hot if its temperature would belong to the 1% hottest days in market j in market m during the base period 1951 to 1980. T-statistics based on robust standard errors clustered by electricity market regions and firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

In Panel A, we add firm-level, electricity market-level, and headquarter level control variables. Panel B controls for the market share of firms, which is defined as the capacity share of firm i in electricity market region m and year t. Panel C controls for the impact of regional gas prices and country-level environmental regulation. Gas price data comes from the EIA for U.S. states and the IEA for all other countries. EPSI is the yearly environmental policy stringency index for the energy industry as published by the OECD. CCPI is the climate policy rating of the Climate Change Performance Index in 2019.

Appendix C. Alternative Model Specifications

Appendix D contains estimates using alternative model specifications. The first, which is presented in Panel A, focuses on the way in which we measure hot weather. In the analysis presented in Table 3, we classify a day as hot if it would belong to the hottest one percent of days in the same region during the base time period (1951-1980). We present specifications redefining our measure classifying a day as hot if it belongs to the hottest 0.5 percent or 2 percent of days in Columns 1 and 2. In Column 3, we use the logarithm of our baseline measure for hot weather and, in Column 4, we use weekly instead of daily temperatures. All alternative specifications lead to similar results.

Panel B shows the results for different measurement periods of hot weather. When we only use the weather in year t-1, the coefficient estimate for hot weather is positive and statistically highly significant, but its magnitude is smaller compared to our baseline specification. This might be related to a noisier approximation of the temperature distribution if only one year is used. The results in Columns 2 and 3, which use the average hot weather between years t-1and t-2 or t-4, are similar to our baseline specification. If we use a longer measurement period in Column 5, the coefficient is still positive but statistically insignificant, which indicates that the weather several years ago does not affect investment decisions today.

In Panel C, we show the results for alternative base periods. In our baseline specification, the temperature distribution from 1951 to 1980 is used to classify days as hot. The choice of this base period follows Hansen et al. 2012 and other climate literature. As alternative baes periods, we use 1951 until 1999 (one year before our sample starts), 1970 to 1999, and 1951 to 2016. None of these adjustments has a substantial impact on the coefficient estimate for hot weather.

Panel D uses alternative concepts to measure hot weather. In our baseline specification, we use the top one percent of the temperature distribution in the base period to classify days as hot. In Column 1, we use an absolute threshold of 25 degrees Celsius to classify a day as hot. Alternative thresholds of 30 and 35 degrees Celsius are used in Columns 2 and 3. Column 4 does not use the temperature itself, but cooling degree days to measure hot weather. Cooling degree days (CDDs) are an important measure in the energy industry since they capture the cooling demand on a specific day, which is highly related to electricity demand. CDDs are calculated as the difference between the daily average temperature and 65F (18.3 degree Celsius) and set to zero if the daily average temperature is lower than 65F. All four alternative measures for hot weather have a positive and statistically significant impact on investments.

Panel E contains estimates using alternative definitions for flexible investment. In our baseline specification, we scale the total capacity of planned flexible power plants by the capacity of the existing generation assets in the same region. In Column 1 we use a dummy variable that equals one if a firm has any investments in flexible plants and zero otherwise. In Column 2, we use the non-scaled natural logarithm of one plus the total capacity of planned flexible plants. Columns 3 and 4 focus on the number of plants instead of their capacity. In these specifications, we use the number of planned flexible plant projects, scaled by the number of existing plants, and the natural logarithm of one plus flexible plant projects. The estimates in each specification suggest that hot weather leads to more investments in flexible power plants.

Panel F uses an alternative clustering of standard errors. In our baseline specification, we double cluster standard errors by electricity market and firm. We cluster by electricity markets alone in Column 1, by electricity market, firm, and year in Column 2, by country in Column 3, and by country and firm in Column 4. All specifications lead to highly significant results.

Appendix D: Robustness to alternative specifications

Panel A: alternative measurement of hot weather				
Column	1	2	3	4
Abnormal hot weather 0.5% $^{m}_{t-1,t-4}$	**0.97*****			
	(2.85)			
Abnormal hot weather 2% $^{m}_{t-1,t-4}$		**0.70*****		
		(2.95)		
Log(Abnormal hot weather $^{m}_{t-1,t-4}$**)**			**0.018*****	
			(4.85)	
Abnormal hot weather (week) $^{m}_{t-1,t-4}$				**0.68*****
				(3.00)
Year-FE	yes	yes	yes	yes
Firm x region-FE	yes	yes	yes	yes
Observations	4,898	4,898	4,869	4,898
Adj. R^2	0.54	0.54	0.54	0.54

Panel B: alternative measurement period for hot days				
Column	1	2	3	4
Measurement period	t-1	t-1,t-2	t-1,t-4	t-1,t-5
Abnormal hot weather $^{m}_{t-1,t-4}$	**0.34*****	**0.83*****	**0.76****	**0.63**
	(4.37)	**(4.62)**	**(2.07)**	**(1.46)**
Year-FE	yes	yes	yes	yes
Firm x region-FE	yes	yes	yes	yes
Observations	4,898	4,898	4,898	4,898
Adj. R^2	0.54	0.54	0.54	0.54

Panel C: alternative base period for the classification of hot days			
Column	1	2	3
Base period start	1951	1970	1951
Base period end	1999	1999	2016
Abnormal hot weather $^{m}_{t-1,t-4}$	**1.05*****	**1.02*****	**1.28*****
	(3.68)	**(3.76)**	**(2.99)**
Year-FE	yes	yes	yes
Firm x region-FE	yes	yes	yes
Observations	4,898	4,898	4,898
Adj. R^2	0.54	0.54	0.54

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Table Appendix D continued

Panel D: alternative measurement of hot weather				
Column	1	2	3	4
Log(days$\geq$ 25$C^{m}_{t-1,t-4}$)	**0.49****			
	(2.05)			
Log(days$\geq$ 30$C^{m}_{t-1,t-4}$)		**0.36****		
		(2.11)		
Log(days$\geq$ 35$C^{m}_{t-1,t-4}$)			**0.89****	
			(2.52)	
Log(CDD$^{m}_{t-1,t-4}$)				**0.030****
				(2.29)
Year-FE	yes	yes	yes	yes
Firm x region-FE	yes	yes	yes	yes
Observations	4,898	4,898	4,869	4,898
Adj. R^2	0.54	0.54	0.54	0.54

Panel E: alternative measurement of flexible investment				
Column	1	2	3	4
	dummy	log(mw)	number	log(number)
Abnormal hot weather$^{m}_{t-1,t-4}$	**2.29*****	**17.6*****	**0.49****	**3.71*****
	(2.86)	**(4.01)**	**(2.40)**	**(3.59)**
Year-FE	yes	yes	yes	yes
Firm x region-FE	yes	yes	yes	yes
Observations	4,898	4,898	4,898	4,898
Adj. R^2	0.62	0.62	0.55	0.66

Panel F: alternative clustering of standard errors				
Column	1	2	3	4
	market	m/id/year	country	country/id
Abnormal hot weather$^{m}_{t-1,t-4}$	**0.96*****	**0.96*****	**0.96*****	**0.96*****
	(3.33)	**(4.26)**	**(2.86)**	**(3.27)**
Year-FE	yes	yes	yes	yes
Firm x region-FE	yes	yes	yes	yes
Observations	4,898	4,898	4,898	4,898
Adj. R^2	0.54	0.54	0.54	0.54

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Table Appendix D continued

The baseline specification is as follows: the dependent variable is FLEXIBLE INVESTMENT$_t^{i,m}$, which is defined as planned flexible power plant construction projects (in megawatt, MW) of firm i in the electricity market region m and year t, scaled by the capacity of existing power plants (in MW) of firm i in market m and year t. Gas, oil, and pump storage power plants are classified as flexible plants. ABNORMAL HOT WEATHER$_{t-1,t-4}^{m}$ is the annual fraction of hot days over the three-year period from $t-1$ to $t-4$ in electricity market m minus 1% (the fraction of hot days during the base period). A day is classified as hot if its temperature would belong to the 1% hottest days in market m during the base period 1951 to 1980. T-statistics based on robust standard errors clustered by electricity market regions and firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively.
In Panel A, alternative measure for hot weather are used. In Columns 1 and 2, we use the hottest 0.5% and 2% during the base period to define hot days. In Column 3, we use the log of our main weather measures. In Column 4, we use weekly instead of daily temperatures. In Panel B, we apply alternative measurement periods for hot days. Panel C shows the results for alternative base periods to define hot days, and Panel D applies alternative measures for hot/extreme weather. In Column 1, we use a measure that captures both hot and cold days. In Columns 2 to 4, we use the change of days with a maximum temperature above 25/30/35 degrees Celsius between the base period and year t in market m. In Panel E, alternative proxies for flexible investments are used. In Column 1, we use a dummy variable which equals one if there is any investment in flexible plants in of firm i in region m and year t, and zero otherwise. In Column 2, the unscaled capacity of planned flexible power plants is used as dependent variable. The dependent variable in Column 3 is the number of planned flexible plants scaled by the number of existing plants. The logarithm of the unscaled number of plants is used as dependent variable in Column 4. Panel F shows the results if we cluster standard errors by market, market plus firm plus year, country, or country plus firm. A detailed description of all variables can be found in Appendix A.