Climate Change, Operating Flexibility, and Corporate Investment Decisions

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Abstract

Extreme temperatures and less predictable weather 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. Using a large international sample of planned power plant projects, we measure the way that electric utilities’ investment decisions depend on the frequency of extreme temperatures. We find that electricity-producing firms invest more in regions where temperatures are becoming more extreme, mostly in flexible power plants that can easily adjust their output. Our results suggest that climate change is becoming a meaningful factor affecting firms’ behavior.

JEL classification: G30, G31

Key words: Climate change, extreme temperatures, firm investment, operational flexibility, electricity generation, power plants

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1. Introduction

The G20 recently called climate change “one of the greatest challenges of our time”. More federal money was spent on the consequences of the volatile weather during 2012 than on education or transportation; globally, the economic losses related to weather events such as prolonged periods of drought, heat waves, cold snaps, and more frequent natural hazards like tornados amounted to about $150 billion.\(^1\) Increasing temperatures and more extreme weather conditions in many regions of the world will lead to dramatic changes in society and the economy, and we are only beginning to understand the nature of these changes.

This paper investigates how firms respond to more extreme weather conditions through investments and changes to their asset structure. We focus on one industry for which detailed asset-level data on investment decisions is available: the electricity producing industry. This industry is meaningfully affected by weather changes: more extreme temperatures and less predictable weather leads to larger fluctuations in electricity demand and the wholesale price of electricity, which in turn affects the optimal production process for firms to use. More flexible methods of electricity production such as gas-fired power plants become more valuable for firms because these plants can quickly react to price changes, in contrast to production technologies such as coal-fired or nuclear plants.\(^2\) Operating flexibility becomes more important

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\(^2\) Electricity producers continually turn on and off their power plants as a function of the prices they face, and the cost of adjusting production varies substantially by method of production (see Reinartz and Schmid, 2016 for more details).
for energy firms when weather conditions become more extreme because flexibility allows producers to adjust output in response to unexpected changes in electricity demand and prices.

Using a very unique database that contains detailed information about plant level investments and investment plans of electricity generating firms around the world, we consider a sample of 273 publicly traded electricity-generating firms which are active in 43 deregulated regions with wholesale markets for electricity between 2000 and 2016. These firms 37,965 unique power plants, and plan to construct 4,425 new power plants during our sample period. We evaluate the extent to which these investment decisions are affected by extreme weather conditions. We measure the impact of the frequency of extreme hot or cold temperatures on the quantity of firms’ investments in new power plants, as well as the type of power plants that these firms build. Our focus is on flexibility of the new power plants to change output quickly and at low cost, since higher wholesale price volatility makes such flexibility more valuable.

Using asset-level data from the Platts World Electric Power Plant database to analyze investment decisions in power plants has at least three advantages relative to accounting-based measures of investment such as Capital Expenditures. First, our data cover early-stage power plant projects at the planning-stage, so we know exactly when each firm makes its investment decision. Second, we know the exact location of the planned plant. We use this locational information to identify the effect of local changes of weather conditions on investment. Information on differences in weather changes across regions allows us to exploit variations in investment decisions across different regions within firms. Finally, we observe the type of the planned power plants since our data provides detailed information on their production technologies. These data allow us to ascertain the flexibility of any particular power plant.

To measure extreme weather conditions, we calculate the frequency of days with extremely hot or cold temperatures in a region (i.e., an electricity wholesale market) and year, using temperature data for individual weather stations from the Global Historical Climatology Network (GHCN). To determine whether a particular temperature is unusual, we compare it to the distribution of temperatures in the same

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3 Most of these markets cover one country, but Australia, Canada, and the U.S. have multiple markets. The Nordpool market area covers the Scandinavian countries Denmark, Finland, Norway, and Sweden.
region in the base period from 1951 to 1980. A day in our sample period 2000 to 2016 is then classified as extreme if it would belong to the hottest or coldest one percent of days in the base period. By this classification scheme, the expected value for this variable would be two percent if weather conditions did not change between the base period and our sample period. Empirically, we find that about 2.8 percent of all days in the sample period are classified as extremely hot or cold, which represents a 40 percent increase relative to the base period.

Theoretically, an increase in extreme weather conditions could lead to more volatility in the demand for electricity. The weather, and temperatures in particular, are key drivers of electricity demand due to heating and cooling demands (Perez-Gonzalez and Yun, 2013). Because electricity storage is not possible in economically meaningful terms, changes in demand typically lead to large changes in electricity prices. For this reason, more extreme weather conditions usually cause electricity price volatility to increase, which in turn makes utilities’ operating flexibility more valuable. Flexible methods of electricity generation, such as gas-fired power plants, can adjust their output quickly and at low cost when electricity prices change. In contrast, inflexible plants, such as coal-fired plants, have high fixed cost and require long time to increase or decrease production volume.

We evaluate the hypothesis that firms invest more in flexible power plants in regions in which temperatures become more extreme. More extreme temperatures, together with the more volatile electricity prices that occur because of these extreme temperatures, make operating flexibility in the form of flexible power plants more attractive for energy firms for two reasons. First, more supply flexibility is needed to cope with higher demand volatility and to avoid system breakdowns (“blackouts”). Second, more volatile electricity prices lead to a higher value of flexible power plants. Consider, for example, the 2015 heat wave

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4 The choice of the base period follows the climate literature (e.g., Hansen et al., 2012)
5 In robustness tests, we use other thresholds for the classification, such as the hottest/coldest 0.5 percent, 2.5 percent, or 5 percent, and we use weekly instead of daily temperatures.
6 As we will show later on, we find strong empirical evidence about the link between weather condition and electricity price volatility.
7 Flexible (gas) plants can profit from higher electricity price volatility because they have relatively low fixed cost but high variable cost, compared to other power plant types. Thus, they can be interpreted as being similar to call options on the electricity price, with marginal cost as strike price and fixed cost as option premium.
in Texas, during which there was a record high demand for electricity, suggesting that an increase in flexible capacity would be valuable to electricity producers to cope with demand and exploit high prices.\(^8\) Thus, when temperatures and electricity prices become more volatile, we expect firms to invest more in flexible production to increase their levels of operating flexibility.

The prediction that higher price volatility increases investment in flexible generation is largely related to the positive impact of uncertainty on the value of flexible power plants. For other types of plants, models which assume irreversible investments generally show that higher uncertainty increase the real option value of waiting, leading to lower levels of investments (McDonald and Siegel, 1986; Dixit and Pindyck, 1994). Firms should invest less in non-flexible plants if weather conditions become more extreme and electricity prices more volatile. However, models that take time-to-build into consideration, 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). These models would not predict any impact of uncertainty on investment in inflexible power plants.

Another prediction we examine is that firms could want to increase their investments in renewable power plant types like hydro, wind, or solar to reduce their CO2 emissions in regions in which climate change is more severe. In these regions, public pressure is likely to be especially high on firms to act in an environmentally friendly manner. There is no clear prediction for total investments as the effect of pressure to reduce emissions on overall investment in power plants is the sum of its impact on different types of power plants, each of which is likely to be different from one another.

We find that utilities tend to increase their investments in flexible power plants in regions in which weather conditions are becoming more extreme. When we exploit variations of weather conditions across regions and time, the estimates imply that the capacity of planned flexible power plants, scaled by the total existing generation capacity, increases by 0.8 percentage points if one percent more days have extreme weather. This one percent increase is approximately the change of the fraction of extreme days between the

\(^8\) [http://www.reuters.com/article/us-texas-electricity-idUSKCN0QG1H320150811](http://www.reuters.com/article/us-texas-electricity-idUSKCN0QG1H320150811)
base period and our sample period and the implied increase equals 10% of the average flexible investment. The model predicts that a one-standard deviation increase in the fraction of extreme days increases flexible investment by about 2 percentage points, which corresponds to a relative increase of 25 percent. If we focus exclusively on the variation of weather conditions over time in a particular market region, the point estimates are slightly smaller and imply that a one-standard deviation increase in the fraction of extreme days increases investments in flexible plants by 1.2 percentage points. The outcome is similar if we only focus on variations across regions within a firm by including firm times year fixed effects. The inclusion of control variables such as regional GDP or firm-level factors (which are already controlled for in the model with firm times year fixed effects) has also no material impact on the results. These results imply that electricity producing firms increase their investments in flexible power plants as response to more extreme weather conditions.

For inflexible power plants, we find no evidence of any effect of extreme weather conditions. For renewable plants, we find a negative point estimate, which is not statistically significantly different from zero. The results suggest that neither investments in inflexible nor renewable plants are materially affected by extreme weather. Given the strong positive impact on flexible investments and the non-effects for inflexible and renewable plants, it is not surprising that the aggregate effect on total investments is positive as well.

We conduct multiple robustness tests for the result that more extreme weather conditions increase planned investments in flexible generation. For example, we use alternative ways to measure extreme weather conditions, alternative definitions of planned investments (e.g., based on the number instead of the capacity of power plants), additional control variables which capture capital market development, electricity market characteristics, or other aspects of a firm’s production assets. We also subsequently exclude all single markets to make sure that we document a general effect which is not driven by one particular region. All of these tests lead to similar results to those using our main specification.

We also investigate how the investments in flexible power plants affect firms’ operating flexibility. We find that firms increase their operating flexibility substantially in regions in which weather conditions
become more extreme. This result holds regardless of whether we use the planned change in flexible production capacity, or the actual change in flexible production capacity over the next four years. When we analyze which firms invest in flexible power plants as response to more extremely hot or cold days, we find that the building-up of flexible production capacity is concentrated in firms with a low level of existing operating flexibility. These results suggest that firms react to more extreme weather conditions by adjusting their production portfolio towards more operating flexibility.

A possible mechanism why firms adjust their production portfolio in this manner is that more frequent extreme weather conditions increase the volatility of electricity demand and prices, which in turn could lead firms to favor production techniques for which quantities can be adjusted quickly and at low cost. The logic of this argument depends on more extreme weather conditions being associated with more volatility of electricity demand and prices. Since electricity demand is difficult to observe, our empirical mechanism tests focus on electrify price volatility. Our measures for electricity price volatility are based on hourly electricity prices in the different wholesale markets, which were manually collected. We define electricity price volatility as the standard deviation of hourly electricity prices in a particular year, scaled by the average electricity price in a market region, and use the logarithm of this variable in our regressions.

We find evidence that more extreme weather conditions do lead to higher electricity price volatility. This pattern holds if we conduct the analysis on the firm-region-year level or if we collapse the data by region and conduct the tests on the region-year level. The point estimates suggest that a one-standard deviation increase of the frequency of extremely hot or cold days lead to an electricity price volatile increase of about 15 percent. When we use electricity price volatility directly as independent variable in models that explain planned investments in flexible generation, we find estimates that are consistent with those discussed above: higher price volatility increases planned investments in flexible and all plants, but has no impact on inflexible of renewable generation. Thus, higher electricity price volatility due to more extreme weather conditions is a likely channel for firms’ increases in planned investments in flexible generation.

Although this study focuses exclusively on energy utilities, our results potentially have implications for other industries as well. While the nature of the impact of extreme weather conditions 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, operating flexibility will likely play a key role for
many firms, not only for energy utilities, to react to new climatic conditions. Firms from many industries
will have to cope with adjustments of their production process,9 disruptions to their supply chains,10 less
predictable consumer demand,11 shifts of consumer preferences,12 or new regulations13 as result of more
extreme weather conditions. The real effects of climate change on businesses in many industries are likely
to be consequential, and are not well understood at this point.

Our analysis extends the literature in a number of ways. First, we provide asset-level evidence on
firms’ investment decisions. In contrast to traditional measures like Capital Expenditures, this asset-level
data allows us to measure details about the investment project, such as production technology it uses and
its exact location. Furthermore, this approach enables us to approximate the time when the decision to invest
was made better because we can observe early-stage projects. This novel measure allows us to contribute
to the investment literature. In particular, this study is related to prior work which investigates how
investment is linked to political uncertainty (e.g., Abel, 1983; Dixit and Pindyck, 1994; Bloom, 2009; Julio
and Yook, 2012; Gulen and Ion, 2016), economic volatility (e.g. Giroud and Mueller, 2019) or product
market characteristics (e.g., Dixit, 1980; Akdogu and MacKay, 2008; Frésard and Valta, 2016). By doing
so, our paper also adds to the broader literature of determinants of corporate investment (e.g., Gan, 2007a,b;
Billett, Garfinkel, and Jiang, 2011; Bolton, Chen, and Wang, 2013; Giroud, 2013; Harford and Uysal,
2014). We extend this literature by showing that weather conditions as a macro factor can have a strong
explanatory power for firm-level investments. By focusing on the establishment network of the firms and

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9 Many firms in the food production industry need to adjust their production process to changing climatic conditions
10 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).
11 Sales of beer or bottled water is strongly linked to weather conditions during the summer months in many countries
12 The tourism industry needs to adjust its “assets” because consumers’ demand shifts to different regions
13 Chinese steel producers have to cope with tougher environmental regulations to reduce pollution levels
within firm investment decisions, our paper also contribute to the recent literature on firm networks and investments (e.g. Giroud and Mueller, 2015; 2018).

Second, the paper contributes to a new and emerging line of research on weather, climate risk and finance. For instance, in their early works, Hirshleifer and Shumway (2003) find a positive relation between sunshine and market returns. More recently, Krueger et al. (2018) explores how climate changes affects institutional investors’ risk perception. Painter (2019) examines the impact of climate changes on the underwriting fees and initial yields of municipal bond issuance. Murfin and Spiegel (2019) studies the real estate price implications of the rise of sea level. Our paper, to our best knowledge, is the first paper that explores how weather conditions affect corporate investments.

Third, this paper also contributes to a long line of research about the economics of energy utilities. Frésard, Rose and Wolfram (2007), for instance, analyze how deregulation affects the efficiency of energy utilities. Becher, Mulherin, and Walkling (2012) investigate corporate mergers in the energy utilities industry, Perez-Gonzalez and Yun (2013) use energy utilities to measure the value of risk management with derivatives, and Rettl, Stomper, and Zechner (2016) evaluate the importance of competitor inflexibility in this industry. Reinartz and Schmid (2016) analyze the impact of production flexibility on the financial leverage in the electricity-generating industry, and Lin, Schmid, and Weisbach (2019) investigate how price risk due to electricity price volatility and production inflexibility affects firms’ cash holdings.

2. Data description

2.1. Sample of energy utilities

To construct a global sample of energy utilities, we start by combining lists of active and inactive utility companies from Thomson Reuters. We focus on stock market listed utilities because reliable data for unlisted firms is often not available. 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. We perform several steps to clean the sample. 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, the business description obtained from Capital IQ, and additionally conduct manual research on the companies’ business lines. Finally, we eliminate all firms that do not have any operations in regions with wholesale markets for electricity, and we exclude the Russian electricity market because weather-based measures are problematic for a market that spans multiple climatic zones. After applying these selection criteria, we end up with a sample of 292 energy utilities.

Many of these firms are active in more than one electricity market region. Figure 1 shows the example of Vattenfall AB, a Swedish power company with electricity generation capacity in Sweden, Germany, Netherlands, Denmark, the U.K, and Finland. For the construction of our dataset, we consider all electricity market regions in which a firm owns capacity as long as the regional capacity accounts for at least one percent of the total production capacity and the fraction of renewable production capacity in that region is less than 50 percent. On average, every firm is active in about three different electricity markets. Overall, our sample firms are active in 43 electricity market regions from 32 countries, they operate 37,965 unique power plants, and plan to construct 4,425 new plants during our sample period.

2.2. Measuring power plant investments

Data on individual power plants is obtained from the annual versions of the Platts World Electric Power Plant database, which provides information on power plants and their technologies around the globe. It includes information on single power plant units, including their production technologies, capacities, geographic locations, start dates of commercial operation, and their owners/operators.\(^\text{14}\) We obtain the annual version of this database for all years between 2000 and 2016 and manually match each power plant in this database to the energy utilities sample.\(^\text{15}\) About one-third of the worldwide production capacity for electricity matches to our sample firms; the remainder are plants owned by large utilities that are not

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\(^\text{14}\) A detailed description of the database is provided by Platts' Data Base Description and Research Methodology. (www.platts.com/IM_Platts_Content/downloads/udi/wepp/descmeth.pdf). Reinartz and Schmid (2016) contain additional information about it as well as other information about electricity markets.

\(^\text{15}\) We use the yearly version of the database because historical owner/operator information is not included.
publicly listed or plants in non-deregulated regions without wholesale markets for electricity and are excluded from our sample for this reason.

Most important for our purposes, this database does not cover only completed power plants, but also contains information on planned power plant construction projects.\footnote{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 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).} These data on existing power plants as well as planned power plant projects allow us to construct our main investment variables. The variable “FLEXIBLE INVESTMENT” is defined as planned construction projects of flexible power plants (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 the planned capacity exceed existing capacity. Based on generation technology of the planned power plant, we classify those using gas, oil, or pump storage as flexible power plants. The variables “INFLEXIBLE INVESTMENT”, “RENEWABLE INVESTMENT”, and “TOTAL INVESTMENT” are constructed in the same way, but we consider planned inflexible plants (coal and nuclear), renewable plants (wind, solar, hydro, geothermal, biomass, biogas), or all planned plants.

For robustness, we also use alternative variables to measure flexible investment. First, we apply 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. For this variable, we scale the number of planned flexible projects of firm $i$ in region $j$ and year $t$ by the number of existing plants of the same firm in the same region. Fourth, we use the logarithm of the number of planned flexible plants.
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 1,605 projects to construct flexible power plants, which account for a total of 401 GW. The average capacity of planned flexible plants is 216 MW (median: 183 MW). The majority of planned flexible plants are gas and gas combined-cycle plants. For inflexible plants, there are 675 projects with a capacity of 433 GW. The average planned inflexible plant has a capacity of about 810 MW (median: 832 MW), about four times the average capacity of planned flexible plants. For renewables, we identify about 2,035 projects, mostly in wind and hydro plants. Their combined capacity is 183 GW, and the average size of planned renewable plants is 65 MW (median: 23 MW). The “others” group, which includes for example waste plants, is not explicitly considered when we distinguish the power plant types, but these plants are included in our analysis focusing on total investments. In total, there are 4,425 unique investment projects in our sample, which have a combined capacity of 1,046 GW. This amount equals approximately today’s installed electricity generation capacity of the U.S., which is 1,200 GW according to the Edison Electric Institute.

2.3. Measuring extreme 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.\(^{17}\) The variable “EXTREME WEATHER” is then calculated as the fraction of days with an extreme temperature in a particular year and electricity market. A day is classified as extreme if its temperature would belong to the one percent hottest or coolest days during the base period 1951 to 1980.\(^{18}\) In the absence of climatic changes,\(^{17}\) Temperatures are calculated as the average across all weather stations in an electricity market region. This approach is potentially problematic for very large market regions like Russia, which spans multiple climatic zones. As explained before, we therefore exclude Russia from the sample.

\(^{18}\) 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
we would expect to classify one percent of days as extremely hot and one percent of day as extremely cold during our sample period 2000 to 2016, which leads to an expected value for this variable of two percent. For robustness tests, we alternatively classify the hottest and coldest 0.5 percent, 2.5 percent, or five percent as “extreme” days, or we use weekly instead of daily temperatures.

The average values of the extreme weather variable across all markets over time are presented in Figure 2. This figure documents that the fraction of extreme days shows an increasing trend since the end of the base period in 1980, as both the linear and the quadratic fit are upward sloping. During our sample period, 3.4 percent of all days are classified as extreme weather days, which is substantially more than expected if temperatures would be the same as during the base period. If we weight the temperature observations by firms, the fraction of extreme days is 2.8 percent (see Table 2). These observations clearly indicate that extreme weather became more common during the last decades, a development that is likely related to climate change.

2.4. Financial variables

Our source for financial variables is Worldscope. The control variables which we use 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), cash holdings (cash and short-term equivalents scaled by total assets), the logarithm of GDP per capita in the country of the respective electricity market, and the inflation rate. All financial variables are winsorized at the 1% and 99% levels. A detailed description of all variables can be found in Appendix A.
2.5. Descriptive statistics

Table 2 presents descriptive statistics for our sample firms, averaged for the whole sample period. On average, the planned investments in flexible power plants account for 7.9 percent of the existing capacity of energy utilities. The respective numbers for investments in inflexible and renewable plant projects are 4.9 percent and 5.5 percent. If we consider all power plant projects, investments account for 17.8 percent of the existing capacity. On average, 2.8 percent of all days are classified as days with extreme temperatures. The firm-level variables indicate that the energy utilities in our sample are comparatively large, with average total assets of about 26 billion USD.

3. Estimating the impact of extreme weather conditions on utilities' investments

3.1. Empirical specification

The fact that many energy utilities operate in more than just one region allows us to observe multiple investment decisions of the same firm in the same year. The example of Vattenfall AB is illustrated in Figure 1. As of 2014, the Swedish power company owns production assets in Sweden, Denmark, Netherlands, Germany, the U.K. and Finland. It is also worth noting that the production assets of Vattenfall are quite heterogeneous across its different regions. For instance, hydro power accounts for about one-third of the generation in Sweden, but less than 10% in Germany. Due to these multiple regions per energy utility, we can observe multiple extreme weather–investment combinations for the same firm in the same year, so can identify the impact of weather changes in one part of the world, holding other factors constant.

We estimate an equation predicting investment for a particular firm in each region in which it operates. We first present a specification with just year effects. This specification has the advantage of utilizing both time series and cross-sectional variation in extreme weather. However, it does not control for firm or region level variables. We next estimate a specification that contains year, region, firm, and firm times region fixed effects. This specification only exploits variations in the frequency of extremely hot or cold days within a particular market region in which a firm operates. Finally, we estimate a specification
that includes firm times year fixed effects. This specification exploits the fact that many firms in our sample, like Vattenfall, operate in more than one region. All standard errors are clustered by country and year.

3.2. Estimates of the impact of extreme weather on investments

We present estimates of these specifications in Table 3. We start with investments in flexible power plants (gas, oil, and pump storage) in Panel A. Theoretically, extreme weather should affect investments in these types of power plants since they can better adjust production levels when demand changes because of changing weather. All columns include year-fixed effects; Columns 2 and 3 include firm, region, and firm times region fixed effects, and Column 4 additionally includes year x firm-fixed effects. In each specification, the estimated coefficient for extreme weather is positive and statistically significantly different from zero. This positive coefficient indicates that firms’ investments in flexible power plants are higher in regions in which temperature are more extreme.

The magnitude of the coefficient for extreme weather is 0.87 when both time-series and cross-sectional variation are used. When we only exploit variation of extreme weather over time, the estimated coefficient is between 0.51 and 0.55, depending on whether controls and firm times year fixed effects are included or not. These estimates imply that a one-standard deviation change of the frequency of extremely hot days leads to a 1.3 to 2.3 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 7.9 percent, these estimates imply a relative increase of 16 to 28 percent. The estimates also imply that flexible investment increases by 0.5 to 0.9 percent points if one percent more days exhibit extreme weather than in the base period. Thus, this effect is not only statistically significant, but also large enough to be economically relevant. The effect of the control variables is in line with expectations: large firms and those with higher market to book ratios invest more on average.

Panel B presents the estimates for inflexible plants (nuclear and coal), renewable plants (wind, solar, hydro, biomass, biogas, geothermal), and all power plants. The coefficient estimates for both inflexible and renewable plants are negative, but they are not significantly different from zero. For all power
plants, we find positive coefficient estimates that are statistically significant. These results suggest that more extreme weather conditions lead an overall increase in investment in power plants that is made up primarily of those with flexible generation technologies.

3.3. Alternative Specifications

Table 4 contains estimates using alternative specifications. The first, which is presented in Panel A, focuses on the way in which of extreme temperatures. In the analysis presented in Table 3, we use the fraction of days with extreme temperatures to construct our measure of extreme temperature. In particular, we classify a day as extreme if it would belong to the hottest or coldest one percent of days in the same region during the base time period (1951-1980). We present specifications redefining our measure of extreme weather classifying a day as extreme if it belongs to the hottest or coldest 0.5 percent, 2.5 percent, or 5 percent of days. The estimates presented in Columns 1 to 3 show that these alternative measures of extreme weather also have a positive impact on investments in flexible plants. In Column 4, we use weekly instead of daily temperatures and find similar results.

Panel B contains estimates using alternative definitions for our dependent variable, which scales the total capacity of planned flexible power plants by the capacity of the existing generation assets in the same region. In Column 1 we instead 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 extreme weather leads to more total investments in flexible power plants.

The third series of robustness tests includes alternative fixed effects (see Panel C). We include year and firm fixed effects in Column 1, year and region fixed effects in Column 2, year plus region plus firm fixed effects in Column 3, and additionally firm times year fixed effects in Column 4. All these specifications indicate that more extreme weather conditions lead to more investments in flexible power
plants. Instead of clustering standard errors by firm and region, Panel D shows the outcome if we cluster standard errors by firm (Column 1), region (Column 2), region and year (Column 3), or region plus year plus firm (Column 4). The results are similar to those of our main specification.

Panel E adds additional controls for regional characteristics besides those already included in Table 3. Although extreme weather is likely to be exogenous to country-level factors, we nevertheless add controls for capital market development in Column 1. These are stock market capitalization and domestic credit to the private sector, both scaled by a country’s GDP. In Column 2, we add the electricity market characteristics total production capacity, average capacity share of flexible power plants, and years since the incorporation the electricity exchange. Columns 3 controls for firm-specific operations in a regional electricity market by adding its production capacity in this market and the share of this market for its total capacity. The estimates using each of these specifications are similar to the ones in Table 3. Finally, Column 4 includes all these additional control variables at the same time, with similar results. The result that extreme weather conditions meaningfully affect firms’ investment appears to be robust to reasonable alternative specifications.

4. The Channel through Which Extreme Weather Affects Investments

4.1. How do extreme weather conditions affect the volatility of electricity prices?

We have documented that changes in extreme temperatures have a meaningful impact on the investments of electric utilities in flexible power plants. In particular, more extreme weather conditions lead firms to increase their construction of new power plants, with the increase coming from plants that rely on relatively flexible production technologies. A likely reason for this pattern is that electricity prices fluctuate with the weather. Extreme weather conditions affect the demand for electricity (Perez-Gonzalez and Yun, 2013) which can lead to large changes in prices. Flexible power plants have the advantage of being able to adjust output quantities quickly and at low cost when there are swings in prices, so become more desirable when weather changes increase expected future price volatility.
To evaluate the extent to which increased electricity price volatility is the reason why more extreme temperatures lead to increased construction of flexible power plants, we examine the underlying hypothesis of this argument: that more extreme weather conditions do in fact increase the volatility of electricity prices. To measure wholesale electricity price volatility, we collect data on electricity prices from different sources, e.g., directly from the websites of the exchanges (see Lin, Schmid, and Weisbach, 2019, for more details). We then calculate electricity price volatility as the standard deviation of hourly electricity prices, normalized by a market’s average electricity price level. The logarithm of this variable is the used in the empirical tests. Electricity prices are measured in US$ per megawatt hour (MWh) and local electricity prices are converted to US$ using daily exchange rates.

In Panel A of Table 5, we estimate the extent to which extreme temperatures lead to higher wholesale price volatility. We estimate this relation at the firm-region-year level, in line with our main tests, and the region-year level. The difference between these approaches is the weighting: while every region-year has the same weight in the region-year analysis, the weight depends on the number of firms which are active in this region in the firm-region-year analysis. In these equations, we include market fixed effects in all specifications because electricity price volatility depends heavily on the market design and is thus hardly comparable across markets.

The estimates are consistent with the notion that more extreme weather conditions lead to more volatile electricity prices. They indicate that a one standard deviation increase in the frequency of extremely hot or cold days leads to an increase of electricity price volatility of about ten percent. The results in Table 5 suggest that the frequency of extreme temperatures has a strong impact on the the volatility of electricity prices, which presumably comes from changes in the underlying demand for electricity.

4.2. How does the volatility of electricity prices affect investments in power plants?

In addition to the way that extreme weather conditions affect electricity price volatility, we also investigate how this price volatility affects planned power plant investments. To do so, we estimate the way that price volatility can affect firms’ power plant investments.
Panel B of Table 5 presents these estimates. They suggest that electricity price volatility leads to more investments in total power plants, which is again in primarily flexible power plants. There is no statistically significant impact of electricity price volatility on investments in inflexible or renewable plants. These results provide further evidence that the positive relation between extreme weather and investments in flexible plants is driven by higher electricity price volatility.

5. The Role of Operating Flexibility

5.1. Change of operating flexibility due to investments

Our hypothesis is that energy firms invest in flexible generation assets to increase their operating flexibility and adjust to more volatility electricity prices. An important issue is the extent to which utilities’ operating flexibility does in fact change because of these investments. To address this issue, we follow two approaches. First, we calculate the difference between a firm’s current operating flexibility and the flexibility it would have once all planned power plants are completed, where we define operating flexibility as the ratio of flexible production capacity to flexible plus inflexible capacity. The second approach considers realized changes in operating flexibility, calculated as the relative change in operating flexibility between now and four years in the future. These comparisons are presented in Table 6, Panel A. This panel documents that more extreme weather conditions increase both the planned and realized change in operating flexibility.

5.2. Existing operating flexibility and investments in flexible plants

An additional prediction is that a firm’s existing operating flexibility should affect the likelihood that a firm plays for its investments in flexible power plants. More volatile electricity prices coming from more extreme weather conditions 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 with existing flexibility.
Panel B of Table 6 presents estimates of equations predicting investments in flexible power plants as a function of firms’ prior 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 two columns, we split the sample into observations with above and below median operating flexibility. Extreme weather conditions have a very strong positive impact on flexible investments for firms with low levels of operating flexibility in Column 1. Although extreme weather also has a positive effect on flexible investments in firms with higher levels of operating flexibility, the coefficient estimate in Column 2 is substantially smaller (0.37 vs 0.84). Using an interaction term for the full sample of firms confirms this result. Both in specifications without (Column 3) or with (Column 4) control variables, we find that extreme weather leads to more investments in flexible plants, but the interaction term between extreme weather and operating flexibility is negative. Assuming a firm with only flexible power plants, these estimates imply that extreme weather conditions would not trigger investments in flexible plants for such a firm with an operating flexibility value of one (coefficient estimates of 1.39 versus -1.40). These estimates suggest that investments in flexible assets are concentrated in firms with lower levels of 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 has potentially become more important. We study the effect of climate change 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. Extreme temperatures and less predictable weather lead to large fluctuations in electricity demand and the wholesale price of electricity.
The fluctuations in demand can affect the optimal production process for firms to use. Much evidence has suggested that climate change can lead to less predictable weather and more extreme temperatures. It is possible that electricity producers respond to more extreme weather by investing in flexible power plants which can adjust to unexpected changes in electricity demand quickly and at low cost.

In this paper, we consider a sample of 282 electricity producing firms operating in 41 electricity markets over the 2000-2016 period. These firms have 4,739 planned power plant projects, of which 1,597 are flexible gas, oil, or pump storage plants. We evaluate the extent to which changes in the regional frequency of extreme temperatures affected our sample firms’ decisions to invest in new power plants. The estimates indicate that the quantity of new, flexible power plants that firms build increases in regions in which temperatures are becoming more extreme. These estimates imply that a one standard deviation increase in the frequency of days with extreme 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. More extreme weather conditions lead to higher electricity price volatility, which in turn makes operating flexibility more valuable for energy utilities.

These results are consistent with the view that the effects of climate change have 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 investments in power plants are an important topic, we hope our paper makes a larger point: changing weather conditions fundamentally changes 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.
References


Figure 1: To illustrate our data structure, this figure shows the main countries in which Vattenfall AB owns production capacity (Source: Vattenfall annual report 2014). In our dataset, we observe Vattenfall’s existing production capacity as well as planned new power plants individually for each country (and year).
Figure 2: Average fraction of days with extreme temperature over time. A day is classified as extreme if its temperature would belong to the 1% hottest or coolest days during the base period 1951 to 1980. A value of 2% indicates that extremely hot or cold days are equally common than during the base period. Linear and quadratic fits are shown in red and green, respectively.

Figure 3: Coefficient estimates for our base model in Column 2 of Table 3 when we subsequently exclude single markets.
Table 1: Descriptive statistics: planned power plant projects

<table>
<thead>
<tr>
<th>Technology</th>
<th>Total number</th>
<th>Total GW</th>
<th>Average MW</th>
<th>Median MW</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Flexible</strong></td>
<td>1,605</td>
<td>401</td>
<td>216</td>
<td>183</td>
</tr>
<tr>
<td>Oil</td>
<td>121</td>
<td>6</td>
<td>50</td>
<td>18</td>
</tr>
<tr>
<td>Gas</td>
<td>715</td>
<td>98</td>
<td>138</td>
<td>65</td>
</tr>
<tr>
<td>Gas comb. cycle</td>
<td>675</td>
<td>271</td>
<td>402</td>
<td>400</td>
</tr>
<tr>
<td>Pump storage</td>
<td>94</td>
<td>26</td>
<td>274</td>
<td>250</td>
</tr>
<tr>
<td><strong>Inflexible</strong></td>
<td>612</td>
<td>433</td>
<td>810</td>
<td>832</td>
</tr>
<tr>
<td>Coal</td>
<td>484</td>
<td>301</td>
<td>623</td>
<td>660</td>
</tr>
<tr>
<td>Lignite</td>
<td>44</td>
<td>22</td>
<td>506</td>
<td>455</td>
</tr>
<tr>
<td>Nuclear</td>
<td>84</td>
<td>109</td>
<td>1,300</td>
<td>1,380</td>
</tr>
<tr>
<td><strong>Renewable</strong></td>
<td>2,035</td>
<td>183</td>
<td>65</td>
<td>23</td>
</tr>
<tr>
<td>Solar</td>
<td>237</td>
<td>9</td>
<td>39</td>
<td>10</td>
</tr>
<tr>
<td>Wind</td>
<td>842</td>
<td>91</td>
<td>108</td>
<td>40</td>
</tr>
<tr>
<td>Hydro</td>
<td>778</td>
<td>75</td>
<td>96</td>
<td>18</td>
</tr>
<tr>
<td>Biogas</td>
<td>67</td>
<td>1</td>
<td>18</td>
<td>8</td>
</tr>
<tr>
<td>Biomass</td>
<td>43</td>
<td>4</td>
<td>83</td>
<td>26</td>
</tr>
<tr>
<td>Geothermal</td>
<td>68</td>
<td>3</td>
<td>48</td>
<td>35</td>
</tr>
<tr>
<td><strong>Other</strong></td>
<td>173</td>
<td>29</td>
<td>224</td>
<td>264</td>
</tr>
</tbody>
</table>

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).
Table 2: Descriptive statistics: firm-level

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>p50</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flexible investment</td>
<td>4978</td>
<td>0.079</td>
<td>0.000</td>
<td>0.207</td>
</tr>
<tr>
<td>Inflexible investment</td>
<td>4978</td>
<td>0.049</td>
<td>0.000</td>
<td>0.184</td>
</tr>
<tr>
<td>Renewable investment</td>
<td>4978</td>
<td>0.055</td>
<td>0.000</td>
<td>0.183</td>
</tr>
<tr>
<td>Total investment</td>
<td>4978</td>
<td>0.178</td>
<td>0.000</td>
<td>0.309</td>
</tr>
<tr>
<td>Extreme weather</td>
<td>4978</td>
<td>0.028</td>
<td>0.019</td>
<td>0.026</td>
</tr>
<tr>
<td>Price volatility</td>
<td>4361</td>
<td>0.726</td>
<td>0.406</td>
<td>1.070</td>
</tr>
<tr>
<td>Log(price volatility)</td>
<td>4361</td>
<td>-0.731</td>
<td>-0.902</td>
<td>0.764</td>
</tr>
<tr>
<td>Assets (USD bn)</td>
<td>3836</td>
<td>25.810</td>
<td>13.383</td>
<td>30.167</td>
</tr>
<tr>
<td>Log(assets)</td>
<td>3836</td>
<td>15.999</td>
<td>16.410</td>
<td>1.863</td>
</tr>
<tr>
<td>Profitability</td>
<td>3833</td>
<td>0.050</td>
<td>0.055</td>
<td>0.074</td>
</tr>
<tr>
<td>Tobin’s Q</td>
<td>3598</td>
<td>1.210</td>
<td>1.141</td>
<td>0.459</td>
</tr>
<tr>
<td>Leverage</td>
<td>3836</td>
<td>0.525</td>
<td>0.535</td>
<td>0.189</td>
</tr>
<tr>
<td>Cash</td>
<td>3836</td>
<td>0.072</td>
<td>0.048</td>
<td>0.082</td>
</tr>
<tr>
<td>Log(GDP per capita)</td>
<td>4621</td>
<td>10.453</td>
<td>10.770</td>
<td>0.844</td>
</tr>
<tr>
<td>Inflation</td>
<td>4621</td>
<td>2.355</td>
<td>2.109</td>
<td>1.912</td>
</tr>
</tbody>
</table>

This table presents descriptive statistics. Reported are the number of observations (N), mean value, median, and standard deviation (SD). A detailed description of all variables can be found in Appendix A.
Table 3: How does extreme weather affect investments in power plants?

Panel A: investments in flexible power plants

<table>
<thead>
<tr>
<th>Column</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extreme weather&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>0.87***</td>
<td>0.51***</td>
<td>0.55***</td>
<td>0.52**</td>
</tr>
<tr>
<td>(3.34)</td>
<td>(4.05)</td>
<td>(3.32)</td>
<td>(2.24)</td>
<td></td>
</tr>
<tr>
<td>Log(assets)&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>0.021*</td>
<td>n/a</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1.75)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Profitability&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>-0.034</td>
<td>n/a</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(-1.21)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tobin's Q&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>0.024***</td>
<td>n/a</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3.65)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leverage&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>-0.040</td>
<td>n/a</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(-0.91)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cash&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>0.11</td>
<td>n/a</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1.66)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log(GDP per capita&lt;sub&gt;t-1&lt;/sub&gt;)</td>
<td>0.33</td>
<td>0.33*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1.53)</td>
<td>(1.70)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inflation&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>-0.0013</td>
<td>0.013*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(-0.62)</td>
<td>(2.02)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Year-FE</td>
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<td>yes</td>
<td>yes</td>
<td>yes</td>
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<tr>
<td>Region-FE</td>
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<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Firm-FE</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Firm x region-FE</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Firm x year-FE</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Observations</td>
<td>4,978</td>
<td>4,931</td>
<td>3,850</td>
<td>2,926</td>
</tr>
<tr>
<td>Adj. R²</td>
<td>0.012</td>
<td>0.56</td>
<td>0.57</td>
<td>0.60</td>
</tr>
</tbody>
</table>

Panel B: investments in other power plants

<table>
<thead>
<tr>
<th>Column</th>
<th>inflex</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extreme weather&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>-0.025</td>
<td>-0.094</td>
<td>0.45***</td>
<td>0.53**</td>
</tr>
<tr>
<td>(-0.34)</td>
<td>(-0.84)</td>
<td>(2.86)</td>
<td>(2.71)</td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Year-FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Region-FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Firm-FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Firm x region-FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Observations</td>
<td>4,931</td>
<td>4,931</td>
<td>4,931</td>
<td>3,850</td>
</tr>
<tr>
<td>Adj. R²</td>
<td>0.71</td>
<td>0.65</td>
<td>0.62</td>
<td>0.65</td>
</tr>
</tbody>
</table>

*continued on next page*
Table 3 continued

The dependent variable in Panel A is FLEXIBLE INVESTMENT, which is defined as early-stage 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 \( t \)). Gas, oil, and pump storage power plants are classified as flexible plants. The dependent variables in Panel B are INFLEXIBLE INVESTMENT, RENEWABLE INVESTMENT, and TOTAL INVESTMENT. Extreme weather is the fraction of days with an extreme temperature in a particular year and electricity market. A day is classified as extreme if its temperature would belong to the 1% hottest or coolest days during the base period 1951 to 1980. All variables are lagged by one year. T-statistics based on robust standard errors clustered by 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: Robustness tests

**Panel A: alternative measurement of extreme weather**

<table>
<thead>
<tr>
<th>Column</th>
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<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extreme weather(_{0.5%t-1})</td>
<td>0.55***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.99)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Extreme weather(_{2.5%t-1})</td>
<td></td>
<td>0.34***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(3.88)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Extreme weather(_{5%t-1})</td>
<td></td>
<td>0.28***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(3.67)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Extreme weather(_{1%,weeklyt-1})</td>
<td></td>
<td></td>
<td>0.38***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(4.12)</td>
<td></td>
</tr>
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</table>

Year-FE: yes yes yes yes
Firm x region-FE: yes yes yes yes
Observations: 4,931 4,931 4,931 4,931
Adj. R\(^2\): 0.56 0.56 0.56 0.56

**Panel B: alternative measurement of flexible investment**

<table>
<thead>
<tr>
<th>Column</th>
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<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extreme weather(_{t-1})</td>
<td>0.75***</td>
<td>6.40***</td>
<td>0.47**</td>
<td>1.40***</td>
</tr>
<tr>
<td></td>
<td>(3.05)</td>
<td>(4.88)</td>
<td>(2.34)</td>
<td>(4.34)</td>
</tr>
</tbody>
</table>

Year-FE: yes yes yes yes
Firm x region-FE: yes yes yes yes
Observations: 4,931 4,931 4,931 4,931
Adj. R\(^2\): 0.61 0.62 0.54 0.64

**Panel C: alternative fixed effects**

<table>
<thead>
<tr>
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<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extreme weather(_{t-1})</td>
<td>0.55***</td>
<td>0.51***</td>
<td>0.50***</td>
<td>0.58**</td>
</tr>
<tr>
<td></td>
<td>(2.84)</td>
<td>(3.99)</td>
<td>(3.72)</td>
<td>(2.27)</td>
</tr>
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</table>

Year-FE: yes yes yes yes
Firm-FE: yes no yes yes
Region-FE: no yes yes yes
Firm x year-FE: no no no yes
Firm x region-FE: no no no no
Observations: 4,967 4,978 4,967 2,968
Adj. R\(^2\): 0.31 0.076 0.35 0.19

*continued on next page*
Table 4 continued

**Panel D: alternative clustering of standard errors**

<table>
<thead>
<tr>
<th>Column</th>
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<th>2</th>
<th>3</th>
<th>4</th>
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<tr>
<td></td>
<td>firm</td>
<td>region</td>
<td>region/year</td>
<td>r/y/firm</td>
</tr>
<tr>
<td>Extreme weather$_{t-1}$</td>
<td>0.51***</td>
<td>0.51***</td>
<td>0.51***</td>
<td>0.51***</td>
</tr>
<tr>
<td></td>
<td>(4.40)</td>
<td>(4.03)</td>
<td>(3.92)</td>
<td>(3.95)</td>
</tr>
<tr>
<td>Year-FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Firm x region-FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Observations</td>
<td>4,931</td>
<td>4,931</td>
<td>4,931</td>
<td>4,931</td>
</tr>
<tr>
<td>Adj. R$^2$</td>
<td>0.56</td>
<td>0.56</td>
<td>0.56</td>
<td>0.56</td>
</tr>
</tbody>
</table>

**Panel E: further control variables**

<table>
<thead>
<tr>
<th>Column</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extreme weather$_{t-1}$</td>
<td>0.56***</td>
<td>0.54***</td>
<td>0.57***</td>
<td>0.56***</td>
</tr>
<tr>
<td></td>
<td>(3.45)</td>
<td>(3.17)</td>
<td>(3.59)</td>
<td>(3.28)</td>
</tr>
<tr>
<td>Stock market to GDP$_{t-1}$</td>
<td>0.00074*</td>
<td>-0.23***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.92)</td>
<td>(-3.32)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Credit to GDP$_{t-1}$</td>
<td>-0.00072</td>
<td>-0.40</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.48)</td>
<td>(-1.65)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log(market production capa$_{t-1}$)</td>
<td>-0.29***</td>
<td>-0.12***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.83)</td>
<td>(-11.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market flexibility$_{t-1}$</td>
<td>-0.27</td>
<td>0.00034</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.07)</td>
<td>(1.12)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market age$_{t-1}$</td>
<td>-0.065***</td>
<td>-0.00043</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.28)</td>
<td>(-1.05)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log(firm production capa$_{t-1}$)</td>
<td>-0.070***</td>
<td>-0.066***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.07)</td>
<td>(-4.82)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market fraction$_{t-1}$</td>
<td>-0.053</td>
<td>-0.053*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.68)</td>
<td>(-1.75)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year-FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Firm x region-FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Observations</td>
<td>3,564</td>
<td>3,830</td>
<td>3,850</td>
<td>3,550</td>
</tr>
<tr>
<td>Adj. R$^2$</td>
<td>0.57</td>
<td>0.58</td>
<td>0.60</td>
<td>0.60</td>
</tr>
</tbody>
</table>

*continued on next page*
The baseline specification is as follows: the dependent variable is FLEXIBLE INVESTMENT, which is defined as early-stage 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 \( t \)). Gas and oil-fired power plants are classified as flexible plants. Extreme weather is the fraction of days with an extreme temperature in a particular year and electricity market. A day is classified as extreme if its temperature would belong to the 1% hottest or coolest days during the base period 1951 to 1980. All variables are lagged by one year. T-statistics based on robust standard errors clustered by regions and firms are presented in parentheses.

In Panel A, alternative measure for extreme weather are used. Their exact definitions can be found in Appendix A. In Panel B, 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 \( j \) (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. In Panel C, we use alternative fixed effects. Panel D shows the results if we cluster standard errors by firm, region, region and year, or region and year and firm. Further control variables (in addition to those in Table 3) are included in Panel E.

***, ** 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: Mechanism: electricity price volatility

**Panel A: extreme weather and electricity price volatility**

<table>
<thead>
<tr>
<th>Column</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>firm-region-level</td>
<td>region-level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Extreme weather&lt;sub&gt;t&lt;/sub&gt;</td>
<td>4.53***</td>
<td>4.34***</td>
<td>3.08**</td>
<td>3.62***</td>
</tr>
<tr>
<td></td>
<td>(3.55)</td>
<td>(3.10)</td>
<td>(2.56)</td>
<td>(3.02)</td>
</tr>
<tr>
<td>Controls</td>
<td>no</td>
<td>yes</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Year-FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Region-FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Firm-FE</td>
<td>yes</td>
<td>yes</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Firm x region-FE</td>
<td>yes</td>
<td>yes</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Observations</td>
<td>4,503</td>
<td>3,363</td>
<td>488</td>
<td>450</td>
</tr>
<tr>
<td>Adj. R²</td>
<td>0.70</td>
<td>0.71</td>
<td>0.71</td>
<td>0.72</td>
</tr>
</tbody>
</table>

**Panel B: electricity price volatility and plant investments**

<table>
<thead>
<tr>
<th>Column</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>flex</td>
<td>inflex</td>
<td>renew</td>
<td>total</td>
</tr>
<tr>
<td>Log(price volatility&lt;sub&gt;t−1&lt;/sub&gt;)</td>
<td>0.035***</td>
<td>0.0051</td>
<td>0.0044</td>
<td>0.033**</td>
</tr>
<tr>
<td></td>
<td>(4.63)</td>
<td>(0.64)</td>
<td>(1.46)</td>
<td>(2.67)</td>
</tr>
<tr>
<td>Controls</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Year-FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Region-FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Firm-FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Firm x region-FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Observations</td>
<td>4072</td>
<td>4072</td>
<td>4072</td>
<td>4072</td>
</tr>
<tr>
<td>Adj. R²</td>
<td>0.58</td>
<td>0.72</td>
<td>0.60</td>
<td>0.65</td>
</tr>
</tbody>
</table>

The dependent variable in Panel A is the logarithm of electricity price volatility. It is defined as the standard deviation of hourly electricity prices, normalized by a market’s average electricity price level. Dependent variables in Panel B are flexible investment, inflexible investment, renewable investment, and total investment. Extreme weather is the fraction of days with an extreme temperature in a particular year and electricity market. A day is classified as extreme if its temperature would belong to the 1% hottest or coolest days during the base period 1951 to 1980. All variables are lagged by one year. T-statistics based on robust standard errors clustered by 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: Which role does operating flexibility play for investment decisions?

<table>
<thead>
<tr>
<th>Panel A: change in operating flexibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Column</td>
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<tr>
<td></td>
</tr>
<tr>
<td>Extreme weather&lt;sub&gt;t-1&lt;/sub&gt;</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Controls</td>
</tr>
<tr>
<td>Year-FE</td>
</tr>
<tr>
<td>Region-FE</td>
</tr>
<tr>
<td>Firm-FE</td>
</tr>
<tr>
<td>Firm x region-FE</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>Adj. R&lt;sup&gt;2&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: existing operating flexibility and investments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Column</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Extreme weather&lt;sub&gt;t-1&lt;/sub&gt;</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Operating flex&lt;sub&gt;t-1&lt;/sub&gt;</td>
</tr>
<tr>
<td>Extreme weather&lt;sub&gt;t-1&lt;/sub&gt; x OpFlex&lt;sub&gt;t-1&lt;/sub&gt;</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Controls</td>
</tr>
<tr>
<td>Year-FE</td>
</tr>
<tr>
<td>Region-FE</td>
</tr>
<tr>
<td>Firm-FE</td>
</tr>
<tr>
<td>Firm x region-FE</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>Adj. R&lt;sup&gt;2&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

The dependent variables in Panel A are planned flexibility change and actual flexibility change. Planned flexibility change is calculated as current plus planned capacity of flexible power plants, relative to current capacity of flexible power plants. Actual flexibility change is the relative change of the capacity of flexible power plants between year t and year t+4. In Panel B, the dependent variable is flexible investment. Operating flexibility is the ratio of flexible production capacity to flexible plus inflexible production capacity. Extreme weather is the fraction of days with an extreme temperature in a particular year and electricity market. A day is classified as extreme if its temperature would belong to the 1% hottest or coolest days during the base period 1951 to 1980. All variables are lagged by one year. T-statistics based on robust standard errors clustered by 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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Investment variables</strong></td>
<td></td>
</tr>
<tr>
<td>Flexible investment</td>
<td>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.</td>
</tr>
<tr>
<td>Inflexible inv.</td>
<td>The construction follows the flexible investment variable. Inflexible power plants are coal and nuclear power plants.</td>
</tr>
<tr>
<td>Renewable inv.</td>
<td>The construction follows the flexible investment variable. Renewable power plants are solar, wind, hydro, geothermal, biomass and biogas power plants.</td>
</tr>
<tr>
<td>Total investment</td>
<td>The construction follows the flexible investment variable. All planned power plants are considered.</td>
</tr>
<tr>
<td>Operating flexibility</td>
<td>Flexible production capacity scaled by the sum of flexible and inflexible production capacity.</td>
</tr>
<tr>
<td><strong>Weather &amp; electricity price variables</strong></td>
<td></td>
</tr>
<tr>
<td>Extreme weather</td>
<td>Extreme weather is the fraction of days with an extreme temperature in a particular year and electricity market. A day is classified as extreme if its temperature would belong to the 1% hottest or coolest days during the base period 1951 to 1980. In the absence of climatic changes, we would expect to classify one percent of days as extremely hot and one percent of day as extremely cold during our sample period, which leads to an expected value for this variable of two percent. Source: Own calculations based on GHCN data.</td>
</tr>
<tr>
<td>Extreme weather$^{0.5%}$</td>
<td>The construction follows the extreme weather variable, but uses the 0.5% of hottest and coldest days during the base period.</td>
</tr>
<tr>
<td>Extreme weather$^{2.5%}$</td>
<td>The construction follows the extreme weather variable, but uses the 2.5% of hottest and coldest days during the base period.</td>
</tr>
<tr>
<td>Extreme weather$^{5%}$</td>
<td>The construction follows the extreme weather variable, but uses the 5% of hottest and coldest days during the base period.</td>
</tr>
<tr>
<td>Extreme weather$^{1%,\text{weekly}}$</td>
<td>The construction follows the extreme weather variable, but uses weekly instead of daily temperatures.</td>
</tr>
<tr>
<td>Volatility</td>
<td>Standard deviation of hourly electricity prices, normalized by a market’s average electricity price level. Electricity prices are in US$ per megawatt hour (MWh). Local electricity prices are converted to US$ using daily exchange rates. Source: Own calculations based on hourly electricity prices.</td>
</tr>
</tbody>
</table>
### Definition of Variables - continued

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Control variables</strong></td>
<td></td>
</tr>
<tr>
<td>Profitability</td>
<td>Earnings before interest and taxes [wc18198] scaled by total assets.</td>
</tr>
<tr>
<td>Tobin’s Q</td>
<td>Market capitalization of equity [wc08001] plus total liabilities [wc03351] scaled by the sum of total liabilities plus book value of equity [wc03501].</td>
</tr>
<tr>
<td>Leverage</td>
<td>Total debt [wc03255] scaled by the sum of total debt plus book value of equity [wc03501].</td>
</tr>
<tr>
<td>Cash</td>
<td>Cash and short term investments [wc02001] scaled by total assets.</td>
</tr>
</tbody>
</table>