Climate Change, Demand Volatility, and Corporate Investment Decisions

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Abstract

How does climate change affect firms' decisions? We investigate how more volatile electricity demand due to more extreme weather affects investment decisions of energy utilities. Using a global sample of early-stage power plant projects, we find that electricity-producing firms invest more in regions in which climate change is more severe. This increase is concentrated in plants using flexible technologies, for which firms can adjust output at relatively low cost. Thus, firms seem to increase their investments to adjust their production assets to changes in demand volatility. Overall, these results are consistent with the view that climate change has far reaching effects on firms' behavior, affecting their investment decisions and undoubtedly many others..

JEL classification: G30, G31

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

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1. Introduction

The G20 recently called climate change "one of the greatest challenges of our time". Increasing temperatures and more extreme weather events in most regions of the world will lead to dramatic changes in society and the economy. While the most commonly discussed effects of global warming are potentially disastrous flooding and changes in the food supply, there are also a plethora of other changes that will occur in the world economy because of climate change. We are only beginning to understand the nature of these changes.

The U.S. Department of Commerce estimates that 70 percent of companies are directly affected by the weather. 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 amounted to about $150 billion.[1] Increasingly extreme weather conditions occurring because of global warming potentially have a major impact on many sectors of the economy. Changing conditions lead to prolonged periods of drought, heat waves, cold snaps, and more frequent natural hazards like tornados. Because changes in climate conditions affect firms' profitability, stock markets as well as regulators become increasingly concerned about the issue, and firms' decisions can be affected by changing climatic conditions. In a survey conducted for CME Group and Storm Exchange, eight out of ten senior finance and risk managers state "that the emergence of global climate change and accompanying volatile weather patterns will require changes to their business models in the decades ahead" (Myers, 2008, p. 4).

This paper investigates how firms respond to climate risk exposure 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 climate change: more extreme and less predictable weather leads to larger fluctuations in the wholesale price of electricity, which in turn affects the optimal production process for firms to use.[2]

[1] Cf. Allianz (2013), p. 7.

[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, or Lin, Schmid, and Weisbach, 2017).

Furthermore, this industry is very concerned about weather risk and has made a systematic attempt to quantify its impact (Myers (2008)).

In this paper, we consider a sample of 384 publicly traded electricity-generating firms from 67 countries between 2000 and 2015, constituting the vast majority of publicly traded electricity-generating firms in the world. These firms operate about 60,000 power plants, and make investments in 13,867 new, early-stage plant construction projects during our sample period. We evaluate the extent to which these investment decisions are affected climate conditions. In particular, we measure the impact of changing weather conditions on the quantity of firms' investments in new power plants, as well as the type of power plants that these firms build.

Using asset-level data from worldwide energy utilities to analyze investment decisions has at least three advantages relative to accounting-based measures like capex. First, our data includes detailed information on early-stage power plant projects, so we know exactly when each firm makes its investment. Second, we know the exact location of a particular plant. We can use this locational information to identify the effect of climate change on investment, since we can measure the change in weather over time in any particular location. Empirically, this information on differences in weather changes across the globe allows us to exploit within firm-year variations in investment decisions across different regions of the world. Finally, and most importantly, we can observe the type of power plant that is built. The *Platts World Electric Power Plant* database provides detailed information on the planned power plants, including their production technology. This information allows us to distinguish between flexible power plants such as gas-fired plants and inflexible generation assets like nuclear or coal power plants.

To measure climate change, we follow the climate literature (e.g., Hansen et al., 2012) and use measures based on the change in the yearly average temperature in a region. As our main measure of climate change, we use the yearly abnormal temperature index which measures the perceived change in temperatures in a region.

Theoretically, climate change could potentially either decrease or increase firms' investments. The first possible effect of climate change, which would lead to fewer investments, is an increase in uncertainty facing the firm. This increased uncertainty could come from a number of factors, including demand for their products, the production processes they should use, or potential new regulations. For instance, climate change could have substantially affect environmental regulations, but if it is difficult to forecast the exact changes, firms could defer investments until the regulations are enacted. Alternatively, electricity producing firms could invest more to adjust their power plant portfolio to the changing conditions, which likely include more extreme weather events and less predictable and more volatile demand for electricity. For example, climate change likely will lead to more events like the 2015 heat wave in Texas, during which there was a record high demand for electricity, suggesting that an increase in capacity could be valuable to electricity producers.[3]

If firms invest more in new power plants in response to climate change, an increase in demand volatility should lead to a change in not only the capacity of power plants, but also their type. First, firms could desire a more flexible supply to avoid system breakdowns ("blackouts") because electricity is not storable.[4] In regions with wholesale markets for electricity, higher demand volatility likely also leads to more volatile prices, which makes flexible power plants more attractive for firms can adjust output at a low cost. For this reason, when weather becomes less predictable, energy utilities will tend to adjust their power plant portfolio towards plants with more operational flexibility, such as gas-fired power plants that can start and stop within minutes. Second, 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. These arguments imply that we should observe more new power plants in regions in which climate change is more pronounced, especially in flexible and/or renewable generation assets.

[3] http://www.reuters.com/article/us-texas-electricity-idUSKCN0QG1H320150811

[4] An overview on the different approaches to balance electricity supply and demand is provided by Hunt (2002), Chapter 7.

Our estimates indicate that utilities tend to increase their investments in new power plants in regions in which climate change is more pronounced. The estimates imply that a one-standard deviation increase in the abnormal temperature index leads to an increase in the capacity of planned plants relative to existing ones of about two percentage points, which equals 12.5% of what investment would be absent climate change. This increase in investment does not appear to be driven by region-specific factors like economic development. These results imply that electricity producing firms increase their investments in new power plants as response to climate change.

To understand the way in which firms change their investment decisions in response to climate change, we examine the type of incremental power plants that they build. Our estimates suggest that changing weather leads utilities to invest more in flexible production assets (e.g. gas-fired power plants) in regions in which climate change is more severe, measuring new investment both in absolute terms and relative to the firm's existing investments. These new plants will tend to increase firms' overall operating flexibility in these regions.

In addition, we examine whether climate change leads to an increase in other types of power plants, especially renewables such as solar or wind power. Our estimates indicate that climate change does not affect investments in other types of power plants such as renewables or inflexible generation assets.

A possible reason why firms adjust their production portfolio in this manner is that climate change could affect uncertainty about electricity demand, which in turn could lead firms to favor production techniques for which quantities can be adjusted at low cost. The logic of this argument depends on larger temperature changes being associated with more extreme weather events, which cause volatility in the demand for electricity. We document that in our sample, changes in average temperatures do lead to more extreme weather events. In addition, we show that for regions with competitive wholesale markets, wholesale electricity price volatility increases with the region's abnormal average temperatures. These results are consistent with the view that flexible power plants, which can start and stop within short periods of time, have become relatively more attractive for energy utilities because of the increase in electricity demand uncertainty, itself a consequence of climate change.

Our results suggest that energy companies adjust their production portfolios to changing weather conditions by increasing the quantity and flexibility of their production facilities. As has been suggested by Al Gore, climate change does create investment opportunities for firms.[5] If we accept that on net, CO_2 emissions have negative social consequences, then an interesting question concerns the way in which the new power plant investments induced by more extreme weather affect emissions. Since coal-fired plants are perhaps the worst offender in terms of CO_2 and also happen to be a relatively inflexible production technique, the incentives produced by climate change toward more flexible production has the social benefit of discouraging coal-fired plans. However, our results do not imply that climate change leads to higher use of renewables. Instead, firms appear to prefer more flexible techniques such as gas-fired plants, which do produce CO_2, but not to as high a degree as coal-fired plants.

Although this study focuses exclusively on energy utilities, our results potentially have implications for other industries as well. Weather-sensitive industries also include the food production industry, which needs to adjust its production process to changing climatic conditions,[6] the tourism industry which needs to adjust its "assets" because consumers' demand shifts to different regions,[7] and other industries like steel that will undoubted face more stringent environmental regulations in the future.[8] While the nature of the impact of climate change 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, 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 capex, this asset-level data allows us

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[5] Stanford GSB Conradin von Gugelberg Memorial Event 2016 (https://www.gsb.stanford.edu/insights/al-gore-business-will-drive-progress-climate-change).
[6] https://www.theguardian.com/environment/2012/sep/19/climate-change-affect-food-production
[7] http://www.ktoo.org/2014/08/04/report-alaska-tourists-may-shift-new-areas-climate-change/
[8] http://www.reuters.com/article/china-steel-environment-idUSL4N0VE3R820150204

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 uncertainty (e.g., Abel, 1983; Dixit and Pindyck, 1994; Bloom, 2009; Julio and Yook, 2012; Gulen and Ion, 2016) or product market characteristics (e.g., Dixit, 1980; Akdogu and MacKay, 2008; Frésard and Valta, 2016).[9]

Second, we are – to the best of our knowledge – the first to investigate how climate change affects firms' investments. Determents for firms' investment decisions that are discussed in the previous literature are, among others, debt capacity and collateral (e.g., Gan, 2007a), bond market access (e.g., Harford and Uysal, 2014), access to bank lending (e.g., Gan, 2007b; Amiti and Weinstein, 2017), corporate governance (e.g., Billett, Garfinkel, and Jiang, 2011), or market timing considerations (e.g., Bolton, Chen, and Wang, 2013). We extend this literature by showing that climate change as a macro factors has a strong explanatory power for firm-level investments.

Third, this paper also contributes to a long line of research about the economics of energy utilities. Fabrizio, 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 (2017) investigate how price risk due to electricity price volatility and production inflexibility affects firms' cash holdings.

[9] Other papers using asset-level data in an investment context include, among others, Gilje and Taillard (2016) who investigate how listing status affects investments in gas drilling projects, Kellog (2014) who analyzes how firms' drilling activities react to changes in uncertainty, and Greenwood and Hanson (2014) who study investment cycles in the shipping industry.

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 2015, 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. For this sample, we collect accounting data like total assets or total debt are obtained from *Worldscope*. After applying these selection criteria, we end up with a sample of 384 energy utilities. These firms operate about 60,000 unique power plants in 67 countries and they conduct 13,867 early-stage power plant construction projects.

Because of the nature of the available weather data (see below), we group the power plants into "regions", which a region is a state or province for all plants in the U.S., Canada, and Australia, and a country for all other plants. There are 135 different regions represented in our sample.

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.[10] We

[10] A detailed description of the database is provided by *Platts' Data Base Description and Research Methodology*.

obtain the annual version of this database for all years between 2000 and 2015 and manually match each power plant in this database to the energy utilities sample.[11] About 50% of the existing plants match to our sample firms; the remainder are owned by large utilities that are not publicly listed 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 early stage construction projects.[12] These data on existing power plants as well as early-stage power plant construction projects allow us to construct our main investment variables. The variable "TOTAL INVESTMENT" is defined as early-stage 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 for values above one and to zero if firm *i* in region *j* and year *t* has existing production capacity of at least one megawatt, but no planned investment.

For robustness, we also use alternative variables to measure total investment. First, we apply a dummy variable that equals one if firm *i* has any early-stage power plant projects in region *j* and year *t*. This variable is set to zero if total investments is zero. Second, we use the unscaled logarithm of one plus the total capacity of all early-stage power plant projects of firm *i* in region *j* and year *t*. Again, this variable is set to zero if firm *i* in region *j* and year *t* has existing production capacity of at least one megawatt, but no planned investment. Third, we consider the number of planned power plants, rather than their capacity. For this variable, we scale the number of planned 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 total number of plants instead of their capacity.

(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.

[11] We use the yearly version of the database because they only include the current owner/operator.

[12] 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).

An advantage of the *Platts* database is that it provides detail on the technology a particular plant uses to produce electricity. This information is important because the flexibility to adjust production levels a low cost is a potentially important advantage when faced with volatile demand for electricity. For this reason, we classify new power plants as flexible, inflexible, or renewable. We classify gas, gas-combined cycle, and oil power plants to be flexible generation assets, coal-fired plants and nuclear plants to be inflexible, and hydro, wind, and solar plants to be renewable generation assets. We also construct firm-level measures which indicate a firm's fraction of existing flexible power plants overall ($FLEXIBILITY_{overall}$) or in a region ($FLEXIBILITY_{region}$). As a measure of the overall flexibility of a firm's plants, we calculate the average "run-up time" for its plants, which measure how long on average a firm's plants take to start up. (see Reinartz and Schmid, 2016, for more details about the construction of run-up time).

Table 1 provides an overview on the early-stage power plant projects, separately for flexible, inflexible, and renewable plants as well as the single technologies therein. There are 4,551 early-stage projects to construct flexible power plants, which account for a total of 1,048 GW. The average capacity of planned flexible plants is about 200 MW, and the projects are located in 96 regions. The majority of planned flexible plants are gas combined-cycle plants. For inflexible plants, there are 1,974 projects with a capacity of 1,167 GW. The average planned inflexible plant has a capacity of about 800 MW, four times the average capacity of planned flexible plants. For renewables, we identify about 6,000 early-stage projects, mostly in wind and hydro plants. Their combined capacity is 670 GW, and the average size of planned renewable plants is 93 MW. The "others" group, which includes for example pump-storage or 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 13,867 unique early-stage investment projects in our sample, which have a combined capacity of 3,057 GW.

2.3. Measuring climate change

Our weather data come from the Global Historical Climatology Network (GHCN). We use the daily average temperatures (GHCN-DAILY) to construct our climate change proxies. Based on approximately 100 million individual observations, we start by calculating the average temperature in degrees Celsius in each region and year from 1951 to 2015.[13] We use the average temperature during the base period 1951 to 1980 for each region as the "base period," and define the ABNORMAL TEMPERATURE in a year and region as the difference between the actual temperature and the average temperature during the base period.[14]

To account for the fact that temperatures can be more volatile in some regions than in others, we also construct the ABNORMAL TEMPERATURE INDEX. For its calculation, we follow Hansen et al. (1998) and divide the abnormal temperature in a region and year by the inter-annual standard deviation during the base period 1951 to 1980 in the same region. Thus, a value of one means that the temperature is one standard deviation higher than the average temperature during the base period.[15]

The average abnormal temperature across all sample countries over time is presented in Figure 2(a). This figure documents that there is a strong temperature increase starting around 2000: from 2000 to 2015, the average abnormal temperature is about 0.6 degrees Celsius. A similar time trend can be observed for the abnormal temperature index in Figure 2(b). The average abnormal temperature index

[13] Temperatures are calculated as the average across all weather stations in a region. We only include weather stations with at least 25 years of data to avoid having newly added stations bias the time trend of the temperature in a region. In Austria, for example, has xx weather stations, so the temperature for Austria on a given day is the average of the temperatures reported by the weather stations on that day. This approach is potentially problematic for larger countries like Russia, which has yyy weather stations. The results are similar if we exclude Russia and China from the sample, which are sufficiently large that the average of the weather stations is not potentially reflective of the weather at any particular location.
[14] 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.
[15] Hansen et al. (1998) state that "[a] value +1 (or -1) is great enough to be noticeable, because a value that large or larger would normally (that is, in the period 1951-1980) occur only about 15% of the time. For example, if the summer is warm enough to yield an index of +1 or greater at a given place, most people who had been living at that location for a long time would tend to agree that it was a "hot" summer." (p. 4114)

during our sample period is slightly above one. Overall, these statistics show that average temperatures have increased substantially during our sample period.

Next, we consider whether there are differences in temperature increases across regions. Figures 3 and 4 present the average abnormal temperature and the average abnormal temperature index for each sample country during sample period. Given the overall increase in temperatures, it is not surprising that most regions experienced higher temperatures during our sample period if compared to the base period 1951 to 1980. Of our 135 regions, 117 experienced a temperature increase and 18 a temperature decrease. The strongest increase in temperature can be found in Europe, Equatorial Africa, and Central America. For several U.S. states close to the West Coast and a handful of countries we find a moderate decrease in the average temperature. The overall picture looks quite similar if we analyze the abnormal temperature index in Figure 4. Overall, this evidence indicates that temperatures on average have risen considerably around the globe, and that these increases are heterogeneous across different regions.

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 plus total debt scaled by the sum of book value of equity plus total debt), 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), and the logarithm of GDP per capita in the headquarter region of the firm. Fiscal years that end between January and June are allocated to the previous year; only complete fiscal years are considered. 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, energy utilities have early-stage investment projects that account for about 16 percent of their existing generation in a region and year. Of these 15 percent, about five percent are related to investments in flexible generation, about three percent to investments in inflexible generation, and renewables account for about eight percent of existing capacity. If we only consider regions in which a firm is investing, we find that investments in flexible generation assets account for about one-third of all investments. The corresponding number for inflexible and renewable investments are 15 percent and 42 percent, respectively.[16] The new projects cause the average run-up time as a proxy for operating inflexibility to decrease by about 0.2. If we compare the old portfolio to the hypothetical new portfolio including the planned power plants, we find that run-up time remains approximately constant.

3. Estimating the impact of climate change on utilities' investments

3.1. Empirical specification

To estimate the effect of the changing climate on utilities' investments, we wish to have a specification that exploits variation in weather, which, at least from the point of view of any particular firm, is exogenous. As is evident from Figures 2 – 5, there is both variation in average temperatures over time and variation across different locations in the magnitude. Our goal is to estimate a specification that takes advantage of this variation in weather changes while at the same time controlling for firm-specific and regional factors.

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, to a small extent, 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

[16] These numbers do not sum up to one because the "other" category, which is also considered for total investment, is not explicitly reported.

these multiple regions per energy utility, we can observe multiple climate change–investment combinations for the same firm in the same year because climate change differs across regions.[17]

We estimate an equation predicting investment for a particular firm in each region in which it operates. We present alternative specifications that vary in their use of firm-level and regional level controls. We first present a specification with just year effects, and one with year effects that contain firm level controls for firm-level factors such as size, profitability, etc. These specifications have the advantage of utilizing both time series and cross-sectional variation in weather. However, they do not control for firm or country level variables that are not captured by characteristics included in the equations. We next estimate a specification that contains year x firm-fixed effects. Because many firms in our sample, like Vattenfall, operate in more than one region, this specification nets out all firm-level effects while still taking advantage of variation in weather across the regions in which the firm operates. However, for firms that only operate in one region, it only utilizes time series variation in weather, and since multi region firms tend to operate in nearby regions with similar weather, the impact of cross-sectional weather variation is minimized. Finally, we present models with firm-region fixed effects, which come with the disadvantage of only exploiting time-series variation in climate change.

3.2. Estimates of the impact of climate change on investment levels

We present estimates of these specifications in Table 3. All columns include year-fixed effects; Columns 3 and 4 additionally include firm-fixed effects and Column 5 includes year x firm-fixed effects.[18] In each specification, the estimated coefficient for the abnormal temperature index (ATI) is positive and statistically significantly different from zero. This positive coefficient indicates that firms invest more in regions in which temperature increases are larger. The magnitude of the coefficient for ATI is between 0.01 and 0.02, which implies that a one-standard deviation change of ATI leads to a 1.5 to

[17] To avoid having tiny markets affecting our findings too much, we exclude regions in which a firms' production assets are less than 1 megawatt of capacity. The results are robust if we include those regions as well.

[18] The firm specific drop out if firm x year fixed-effects are included because these models only exploit variation within a firm and year. For this reason, only firms that have operations in different regions can be considered for this test, which also explains the smaller number of firms in column 5.

3 percentage point increase in the total investment (which is defined as the capacity of early-stage investment projects relative to existing power plants). Because the average total investment is 16 percent, these estimates imply that a one standard deviation increase in temperature corresponds to a 10 to 20 percent increase. Thus, this effect is not only statistically significant, but also large enough to be economically relevant. The effect of the control variables are in line with expectations: large firms, firms with higher market to book, and those with more cash on the balance sheet invest more on average. The coefficients for leverage and the GDP of a firm's headquarter country are negative, but the effect is statistically not significant in the specification with firm-fixed effects.

3.3. Robustness

Tables 4, 5, and 6 contain estimates of alternative specifications, which we include to ensure that that the relation between temperature changes and investment in new power plants are robust to alternative assumptions. The first robustness test in Table 4 focuses on the measurement of climate change. In the analysis presented in Table 3, we measure changes in climate using the abnormal temperature index (ATI). In Columns 1 and 2 of Table 4, we replace this with the average value of ATI over the past three years. If climate change is a slow process a longer-term trend rather than the one year temperature is likely to be informative about future weather conditions, and thus be a better predictor of firms' investment choices. In addition, we reestimate the equation using the abnormal temperature (not standardized) and its 3-year average in Columns 3-6 of Table 4. Both the magnitude and statistical significance of the coefficients on the variables measuring temperature in these alternative specifications are similar to those reported in Table 3.

As a second series of robustness tests, we measure investment in several different ways. Our main measure of investment scales the total capacity of early-stage plant construction projects by the capacity of the existing generation assets. In Column 1 of Table 5 we instead use a dummy variable that equals one if a firm has any investments in a region and year and zero otherwise. In Column 2, we use the non-scaled natural logarithm of the total capacity of all early-stage plant projects (plus one). Columns 3 and 4 focus on the number of plants instead of their capacity. In these specifications, we scale the number of all plant projects by either the number of existing plants, or the natural logarithm of all plant projects (plus one). The estimates in each specification are similar and all suggest that climate change leads to more total investments in new power plants.

The third series of robustness tests includes additional controls for regional characteristics. If these characteristics are correlated with climate change, excluding them from the specification could meaningfully affect our estimates. Although climate change, measured by the *abnormal* temperature in a region, is likely to be exogenous to other country-level factors, we nevertheless add regional macroeconomics and firm-level variables in Columns 1 to 6. The macroeconomic controls are regional GDP (instead of headquarter GDP), GDP growth in a region, and the level of inflation in a region. The firm-level controls are a firm's overall level of flexibility (i.e., capacity of flexible plants to total plants), its flexibility in a region, its total production capacity in a region, and the firm's capacity in this region to its total capacity. The estimates using each of these specifications are similar to the ones in Table 3, and suggest that abnormal temperature indices meaningfully affect firms' investment decisions.

In the Column 7 of Table 6, we add firm-region fixed effects to the specification. These fixed effects effectively control for all time-constant regional characteristics, such as legal origin or anti-director rights. We do not use this model as our main model because it has an important disadvantage: it only exploits time-series variation of our climate change proxy *within* a region. However, climate change is a slow process, so differences *between* regions should be more relevant than changes over short time periods. Nonetheless, the results from this model are similar to our prior findings, although the economic magnitude is smaller.

4. The Channel through Which Climate Change Affects Investment

4.1. Types of power plants

To understand why firms increase investment in response to climate change, we next turn to the issue of the types of power plants in which they invest. As discussed above, climate change is likely to lead to less predictable weather and to more extreme weather events, and thus less predictable and more volatile demand for electricity. Consequently, energy utilities potentially have incentives to adjust their power plant portfolios towards more operational flexibility. One way to increase operational flexibility is by building more gas-fired power plants which can start and stop within minutes. Alternatively, energy utilities could increase their investment in renewable generation assets because of public pressure or stricter environmental regulations to reduce CO2 emissions in regions in which climate change is more severe.

In Table 7, we estimate the way in which changes in weather affect investment in different types of power plants. We construct variables entitled FLEXIBLE INVESTMENT, INFLEXIBLE INVESTMENT, and RENEWABLE INVESTMENT in the same way as TOTAL INVESTMENT, except that that only power plant projects of a particular type are used to construct each variable. In Panel A, we present estimates of equations that predict each type of power plant investment using the same specification as in Table 3.

In the equations predicting investments in flexible power plants in Columns 1 and 2, the estimates indicate that climate change affects investment. The coefficient on the abnormal temperature index is about .01, and is statistically significantly different from zero. This coefficient is of a similar magnitude to the coefficients from the corresponding models for total investment in columns 4 and 5 of Table 2. This fact that the implied increase in flexible investments from a given change weather conditions is about the same magnitude as the overall change suggests that the increase in total investments is driven by investments in flexible production assets, such as gas-fired plants.

In Columns 3 to 6 we estimate the impact of weather changes on investments in inflexible power plants and renewables. In contrast to the estimates for flexible power plants, these estimates indicate that climate change has no effect on investment in inflexible or renewable production assets. The impact of changing weather on investment appears to come from a higher demand for flexible power plants whose output can be varied at low cost.

As an additional way of examining the types of power plants affected by changes in weather, we consider an alternative specification that predicts the relative investments in different kinds of plants. For this specification, we restrict our sample to firm-years in which firms make some investments, and use the fraction of a firm's total investment of a particular type as our dependent variable. We present estimates of equations predicting this fraction in Panel B of Table 7.

The estimates in Panel B of Table 7 are consistent with those in Panel A, and also suggest that increases in temperature lead to investments in flexible power plants, but not inflexible or renewable ones. In the equations in Columns 1 and 2 predicting the fraction of investments in flexible power plants, the coefficient on Absolute Temperature Index is positive and statistically significantly different from zero. In contrast, in the equations in Columns 3 – 6 predicting the fraction of investments in inflexible power plants and renewables, the coefficients on Absolute Temperature Index are small and not statistically significantly different from zero.

Finally, we analyze the extent to which changes in weather lead to overall changes in the production flexibility of a particular energy utility. To evaluate the change in a firm's production flexibility, we rely on a firm's "run-up time" as a firm-level flexibility measure. This variable is defined as the capacity-weighted average time which is necessary to start-up the power plants in hours.[19] Higher values of run-up time go along with less production flexibility because it takes longer to start and stop the plants.

We present estimates of the impact of weather changes in a firm's run up time in Panel C of Table 7. We first analyze the relative difference between the run-up time of early-stage plant construction projects and the existing plants. The results in Columns 1 and 2 indicate that when temperatures increase, the run-up time of the early stage projects tends to be lower than that of firms' existing plants. Consequently, once investments of firms faced with increasing temperatures are completed, their production processes will become more flexible. In Columns 3 and 4, we estimate the effect of

[19] It is based on the production technologies of the firms' power plants. See Reinartz and Schmid (2016) for technology-specific values.

temperature increases on the difference between the average run-up time of the firms' new power plant portfolio (consisting of their early-stage projects together with their existing plants) to that of the existing plants alone. The results again indicate that temperature increase lead the new production portfolios to become be more flexible than firms' existing plants, although the coefficient on Absolute Temperature Index is not statistically significantly different from zero in the specification presented in Column 3.

4.2. How does Climate Change Affect the Volatility of Electricity Demand?

We have documented that changes in climate appear to have a meaningful impact on the investments of electric utilities in new power plants. In particular, higher abnormal temperatures lead firms to increase their construction of new power plants, with the increase coming from plants that rely on relatively flexible production technologies. One potential reason for this pattern is that electricity demand fluctuates with the weather, so that climate change should lead to more volatile demand for electricity.

To evaluate the extent to which increased volatility of electricity demand is the reason why higher temperatures lead to increased construction of flexible power plants, we examine the underlying hypothesis of this argument: whether temperature increases do in fact increase the volatility of electricity demand. To do so, we focus on two implications of this argument that can be empirically verified. First, we investigate whether climate change leads to more extreme weather events. If the increase in average temperature is associated with more extraordinarily hot or cold days, demand for electricity is likely to deviate from normal patterns, making flexible generation assets valuable. Second, we utilize the fact in much of the world, electricity is sold on a wholesale market, whose prices reflect the short-term demand for electricity (see Lin, Schmid, and Weisbach (2017)).[20] If changing weather conditions lead to increased demand volatility, this higher demand volatility should be reflected in higher wholesale price volatility.

To define extreme weather events, we first estimate the average temperature in each month during the 1951 to 1980 period and calculate its standard deviation. Then we calculate the fraction of days

[20] For other regions without wholesale markets for electricity, we also expect that climate change leads to higher demand fluctuations. However, we cannot test the hypothesis in these regions because demand is not observable.

in each year during our sample period for which the temperature was above the historical average plus 2.5 times the standard deviation or below the historical average minus 2.5 times the standard deviation. If we assume that temperatures follow the normal distribution, we would expect that about 1.2 percent of all days are outside this range. The actual fraction of days outside this range, averaged across all sample regions, is shown in Figure 5. We see a clear trend that the fraction of extreme days increases, which indicates that the weather became more extreme over time. While only around one percent of all days are classified as extreme until the 1980s, this fraction increases to about two percent in the 1990s and above three percent in the 2000s.

However, while there is a trend toward increasing temperatures and also a trend to more extreme weather events, it is not clear if the two are related, and if the places in the world with higher increases in temperatures also tend to have more extreme events. In Panel A of Table 8, we estimate equations predicting how abnormal average temperatures in a specified region in a particular year affect the likelihood of extreme weather days. The estimates in this panel imply that a one-standard deviation increase of the abnormal temperature index leads to an increase in of the fraction of extreme days of slightly less than one percentage point. This result is consistent with the notion that climate change leads to more extreme weather.

To measure wholesale electiricity price volatility, we rely on a database of wholesale electricity prices. For each region with a wholesale market, we collect data on electricity prices from different sources (e.g., directly from the websites of the exchanges). We then calculate electricity price volatility as standard deviation of returns of hourly electricity prices in market and year. Returns are calculated as differences between hourly prices in U.S. dollar and standardized by the average price in a market.

In Panel B of Table 8, we estimate the extent to which abnormal temperatures lead to higher wholesale price volatility. Because neither electricity price volatility nor climate change is firm-specific, we estimate, at the region-year level, the extent to which weather volatility leads to wholesale price volatility. In these equations, we include electricity 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 climate change leads to more volatile electricity prices. They indicate that a one standard deviation increase in the Absolute Temperature Index leads to an increase of electricity price volatility of about 0.05. The mean value for electricity price volatility is about 0.4, so an increase of .05 represents a relative change of more than 10 percent. The results in Table 8 suggest that climate change has a strong impact on the occurrence of extreme weather and the volatility of electricity prices, which presumably comes from changes in the underlying demand for electricity.

5. 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. 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. When there is a period of prolonged heat or cold, demand for electricity increases and electricity producers would like to increase their production. Much evidence has suggested that climate change has led to less predictable and more extreme weather events. The effect of climate change on investment is not clear. One possibility is that the uncertainty about future demand will lead firms to postpone or reduce investment. Alternatively, it is possible that electricity producers respond by increasing both their overall capacity for producing electricity, and the methods that they use, so that they can alter output at relatively low cost.

In this paper, we consider a sample of 384 electricity producing firms from 67 countries over the 2000-2015 period. These firms made investments in 13,867 new power plants during our sample period. We evaluate the extent to which changing weather conditions affected their investment decisions. Our analysis exploits both time series and cross-sectional variation in abnormal weather to identify this effect. The estimates indicate the quantity of new power plants that firms build increases in regions in which climate change is more severe. In addition, the estimates suggest that the incremental plants built because of weather are likely to be relatively flexible ones that can adjust output at low cost. These estimates imply that a one standard deviation increase in the abnormal temperature leads to a 10 to 20 percent relative increase in investment, suggesting that changes in weather have had a substantial impact on these firms' investment decisions.

These results are consistent with the view the effects of climate change have been incorporated into 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, which happens to be relatively inflexible, so adjusting output is relatively high cost. 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 be to renewable energy, although there has been an increase in renewables for other reasons. Instead, changing weather conditions have led firms to invest in relatively flexible plants such as gas fired ones, which do produce CO_2 emissions, although fewer than a coal fired one.

While investments in power plants are an important topic, we hope our paper makes a larger point: changing weather fundamentally changes the economics of many businesses. Our results suggest that it leads energy producing companies to increase investments to enhance their operating flexibility. It potentially leads firms to invest more in other industries as well to adjust to the changing conditions, but 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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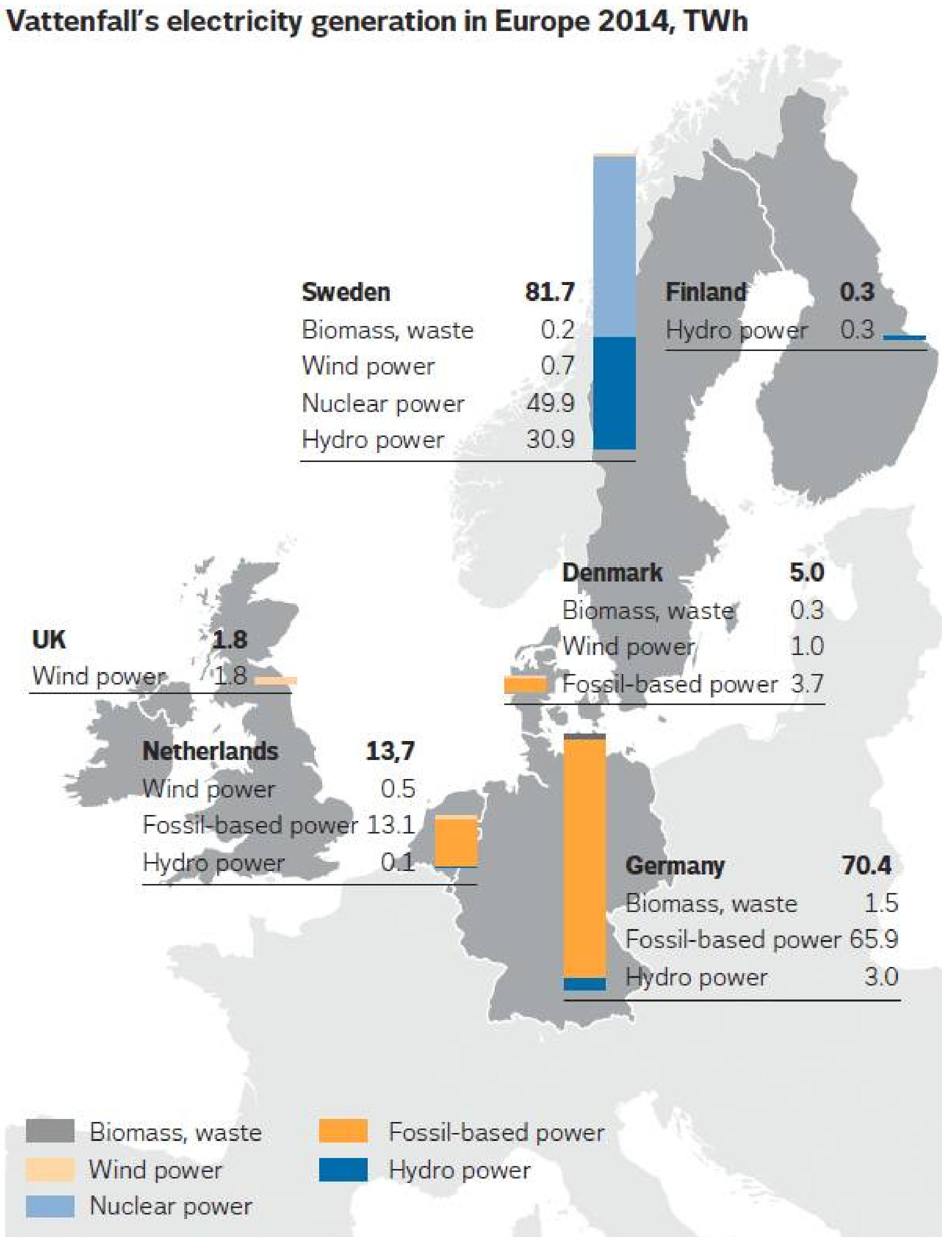
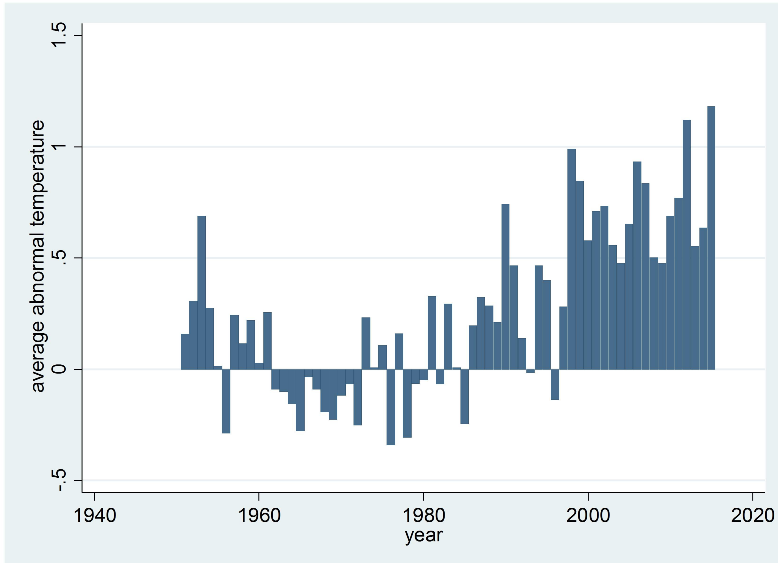
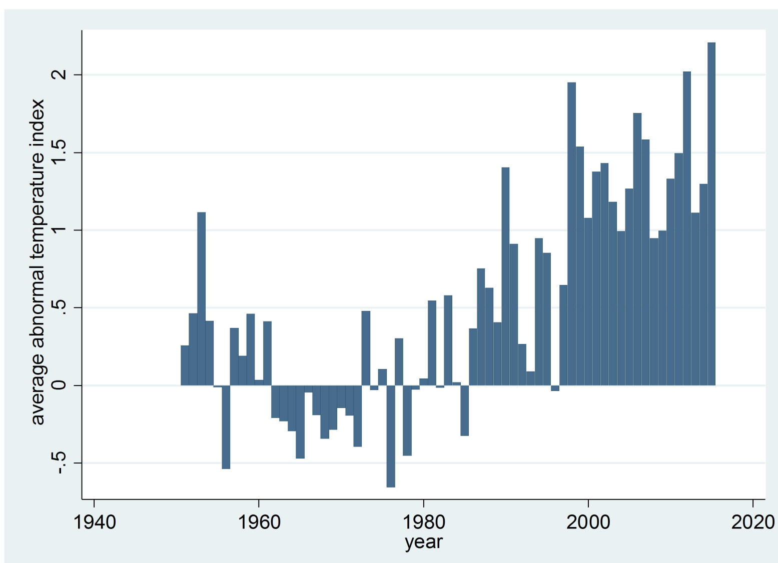


Figure 1: To illustrate our data structure, this figure shows the main countries in which Vattenfall AB owns production capacity (Source: Vattenfall annual report 2014). In our dataset, we would observe Vattenfall's existing production capacity as well as planned new power plants individually for each country (and year).



(a) Abnormal Temperature



(b) Abnormal Temperature Index

Figure 2: This figure shows the development of the average abnormal temperature and the average abnormal temperature index over time. Abnormal temperature for a region (i.e., country or state for U.S., Canada, and Australia) and year is measured relative to the base period 1951 to 1980. The abnormal temperature index is constructed as abnormal temperature divided by the interannual standard deviation during the base period 1951 to 1980 in the same region. More details about its construction can be found in Appendix A.

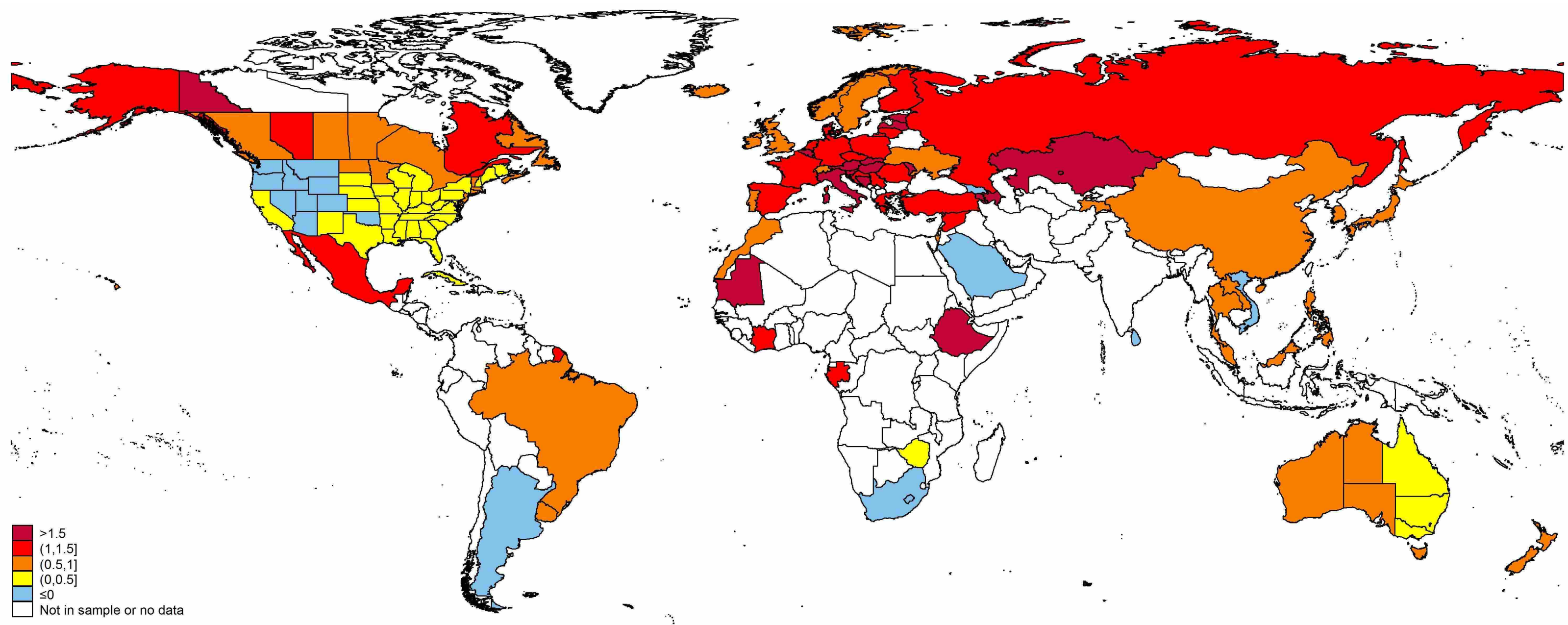


Figure 3: This figure shows the average abnormal temperature during our sample period 2000 to 2015. Abnormal temperature for a region (i.e., country or state for U.S., Canada, and Australia) and year is measured relative to the base period 1951 to 1980. More details about its construction can be found in Appendix A.

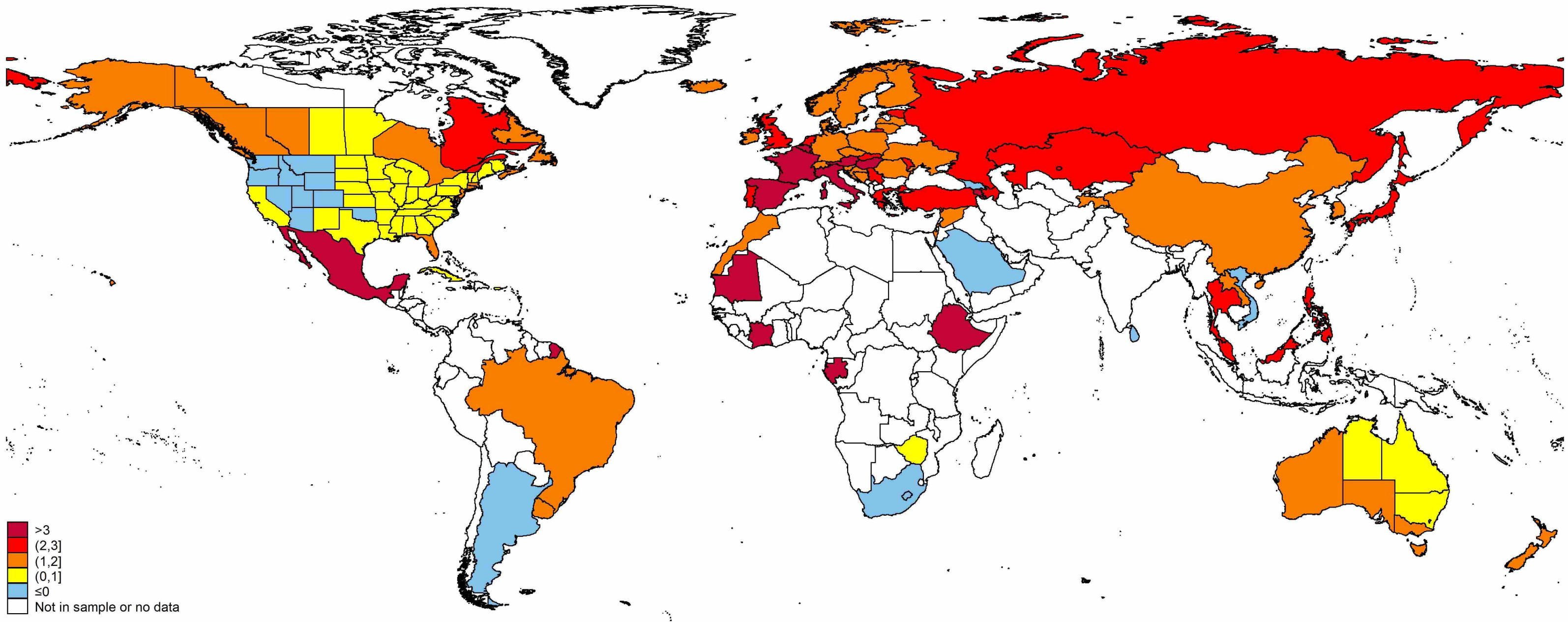


Figure 4: This figure shows the average abnormal temperature index during our sample period 2000 to 2015. The abnormal temperature index is constructed as abnormal temperature divided by the interannual standard deviation during the base period 1951 to 1980 in a region (i.e., country or state for U.S., Canada, and Australia). More details about its construction can be found in Appendix A.

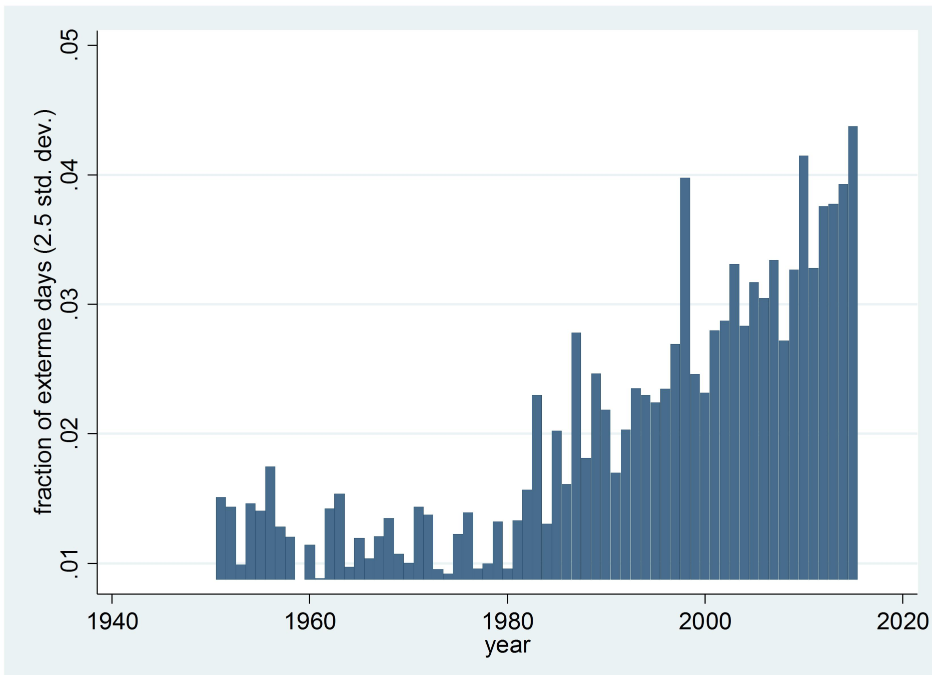


Figure 5: This figure shows the development of the yearly fraction of extreme days over time. A day is defined to be extreme if the average temperature on that day is higher (lower) than the average temperature in the corresponding months during the base period 1951 to 1980 plus (minus) 2.5 times the standard deviation of temperatures during that month in the base period. More details about its construction can be found in Appendix A.

Table 1: Descriptive statistics: Early-stage power plant projects

	total		**capacity (MW)**		**countries**
Technology	**number**	**GW**	**average**	**median**	**number**
Flexible	4,551	1,048	199	124	96
Oil	627	70	112	19	58
Gas	1,841	262	142	83	108
Gas comb. cycle	2,083	716	344	270	121
Inflexible	1,974	1,167	807	850	59
Coal	1,819	1,003	551	600	87
Nuclear	155	165	1,062	1,100	30
Renewable	5,999	670	93	37	92
Solar	635	25	40	13	69
Hydro	2,710	388	143	48	89
Wind	2,654	256	97	50	119
Other	1,352	172	127	70	64
Total	13,876	3,057	291	250	83

This table presents descriptive statistics for the early-stage investment projects. Each project is only considered in the first year in which it appears in the database. Reported are the total number of power plant projects, the total capacity of planned plants in gigawatt, the average and median capacity of planned plants, and the number of regions (i.e., countries or states for the U.S., Canada, and Australia) in which any project takes place.

Table 2: Descriptive statistics: Firms

Variable	Obs	Mean	p25	p50	p75	SD
Investment variables						
Total investment	12,767	0.16	0.00	0.00	0.14	0.31
Flexible investment	12,767	0.05	0.00	0.00	0.00	0.18
Inflexible investment	12,767	0.03	0.00	0.00	0.00	0.13
Renewable investment	12776	0.08	0.00	0.00	0.00	0.24
Flexible to total	4,587	0.34	0.00	0.00	0.81	0.42
Inflexible to total	4,587	0.15	0.00	0.00	0.00	0.32
Renewable to total	4587	0.42	0.00	0.08	1.00	0.47
Δ $\text{RuT}_{new-projects}$	3,400	-0.23	-0.92	-0.39	0.19	0.72
Δ $\text{RuT}_{new-portfolio}$	10,026	0.01	0.00	0.00	0.00	0.24
Weather variables						
Abnormal temp. index	12,767	1.20	0.09	1.12	2.21	1.67
Abn. temp. index (3y avg)	12,105	1.18	0.27	1.07	2.05	1.39
Abnormal temp.	12,767	0.60	0.05	0.61	1.13	0.86
Abnormal temp. (3y avg)	12,105	0.59	0.16	0.59	1.02	0.68
Extreme $\text{days}_{2.5std.dev.}$	12,776	0.024	0.005	0.014	0.027	0.037
Control variables						
Log(assets)	12,767	16.16	14.92	16.71	17.66	1.95
Profitability	12,713	0.05	0.04	0.05	0.07	0.07
Tobin's Q	12,121	1.17	1.02	1.11	1.26	0.40
Leverage	12,767	0.55	0.45	0.56	0.66	0.18
Cash holdings	12,767	0.07	0.02	0.04	0.10	0.07
$\text{Log(GDP/capita)}_{HQ}$	12,141	10.36	10.49	10.77	10.81	0.85

This table presents descriptive statistics. Reported are the number of observations (N), mean value, 25% percentile, median, 75% percentile, and standard deviation (SD). A detailed description of all variables can be found in Appendix A.

Table 3: Climate change and investments in power plants

Column	1	2	3	4	5
Abn. temp. index	**0.021*****	**0.017*****	**0.0088*****	**0.0093*****	**0.012*****
	(6.22)	**(3.88)**	**(3.16)**	**(3.11)**	**(2.95)**
Log(assets)		0.0051		0.033**	n/a
		(0.80)		(2.19)	
Profitability		-0.16		-0.0066	n/a
		(-1.75)		(-0.14)	
Tobin's Q		-0.0068		0.024*	n/a
		(-0.26)		(1.96)	
Leverage		-0.066		-0.053	n/a
		(-1.48)		(-1.13)	
Cash holdings		0.38***		0.23***	n/a
		(3.43)		(4.46)	
Log(GDP/capita)$_{HQ}$		-0.059***		-0.086	n/a
		(-3.15)		(-0.83)	
Year-FE	yes	yes	yes	yes	yes
Firm-FE	no	no	yes	yes	yes
Firm x Year FE	no	no	no	no	yes
Observations	11,637	10,897	11,613	10,876	9,474
Firms	384	357	360	336	163
R2	0.017	0.046	0.26	0.26	0.25

The dependent variable is TOTAL INVESTMENT, which is defined as early-stage 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 abnormal temperature index is constructed as abnormal temperature in a year and region, relative to the base period 1951 to 1980, divided by the interannual standard deviation during the same period. All variables are lagged by one year. T-statistics based on robust standard errors clustered by countries/firms/years 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: measurement of climate change

Column	1	2	3	4	5	6
$\mathbf{ATI_{3y}}$	**0.014*** **	**0.014*** **				
	(3.13)	**(3.51)**				
Temp. index			**0.023*** **	**0.031*** **		
			(3.63)	**(4.63)**		
Temp. $\mathbf{index_{3y}}$					**0.033*** **	**0.034*** **
					(3.31)	**(4.01)**
Log(assets)	0.037**	n/a	0.032**	n/a	0.037**	n/a
	(2.38)		(2.15)		(2.38)	
Profitability	0.0039	n/a	-0.0070	n/a	0.0047	n/a
	(0.089)		(-0.16)		(0.10)	
Tobin's Q	0.027**	n/a	0.023*	n/a	0.027**	n/a
	(2.42)		(1.98)		(2.44)	
Leverage	-0.058	n/a	-0.051	n/a	-0.058	n/a
	(-1.25)		(-1.09)		(-1.27)	
Cash holdings	0.25***	n/a	0.22***	n/a	0.25***	n/a
	(4.95)		(4.54)		(5.00)	
Log(GDP/capita)$_{HQ}$	-0.049	n/a	-0.081	n/a	-0.045	n/a
	(-0.41)		(-0.79)		(-0.38)	
Year-FE	yes	yes	yes	yes	yes	yes
Firm-FE	yes	yes	yes	yes	yes	yes
Firm x Year FE	no	yes	no	yes	no	yes
Observations	10,363	10,038	10,922	10,500	10,363	10,038
Firms	311	163	337	170	311	163
R2	0.25	0.24	0.26	0.24	0.25	0.24

ATI stands for abnormal temperature index. The dependent variable is TOTAL INVESTMENT, which is defined as early-stage 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). All variables are lagged by one year. T-statistics based on robust standard errors clustered by countries/firms/years 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: Robustness test: measurement of investment

Column	1 dummy	2 log(MW)	3 # to total	4 log(#)
Abn. temp. index	**0.10***** **(5.29)**	**0.15**** **(2.87)**	**0.016***** **(2.96)**	**0.093***** **(3.14)**
Log(assets)	0.061**	0.30**	0.0083	0.052
	(2.19)	(2.31)	(0.57)	(1.56)
Profitability	-0.54*	0.29	0.015	0.053
	(-1.69)	(0.69)	(0.52)	(0.81)
Tobin's Q	0.020	0.28**	0.025	0.058*
	(0.27)	(2.60)	(1.37)	(1.81)
Leverage	-0.43***	-0.47	-0.071	-0.15
	(-2.60)	(-1.59)	(-1.68)	(-1.35)
Cash holdings	0.58*	0.48	0.21***	0.45**
	(1.65)	(0.89)	(3.06)	(2.23)
Log(GDP/capita)$_{HQ}$	-0.26***	0.71	-0.16**	0.052
	(-3.57)	(1.44)	(-2.72)	(0.36)
Year-FE	yes	yes	yes	yes
Firm-FE	yes	yes	yes	yes
Firm x Year FE	no	yes	no	yes
Observations	11,747	11,728	10,876	10,876
Firms	363	344	336	336
R2	0.041	0.30	0.22	0.26

The dependent variable is indicated in each column. The dummy equals one if there is any early stage power plant project and zero otherwise. Ln MW is the natural logarithm of all early stage power plant projects (not scaled). # stands for number of power plants projects. In column 3, the number is scaled by the number of total plants of firm i in market j and year t. In column 4, the natural logarithm of this number is used (not scaled). All variables are lagged by one year. T-statistics based on robust standard errors clustered by countries/firms/years 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: Robustness: regional characteristics

Column	1	2	3	4	5	6	7
	macro controls		micro controls		both		+FE
ATI	**0.0084****	**0.011****	**0.010*****	**0.011****	**0.0094****	**0.011****	**0.0053****
	(2.71)	**(2.80)**	**(3.11)**	**(2.78)**	**(2.52)**	**(2.73)**	**(2.62)**
Log(assets)	0.030*	n/a	0.027*	n/a	0.032*	n/a	0.028
	(1.78)		(1.86)		(1.93)		(1.60)
Profitability	-0.014	n/a	-0.0014	n/a	-0.012	n/a	0.0086
	(-0.28)		(-0.036)		(-0.26)		(0.23)
Tobin's Q	0.024*	n/a	0.013	n/a	0.016	n/a	0.012
	(1.93)		(1.13)		(1.32)		(0.93)
Leverage	-0.043	n/a	-0.040	n/a	-0.037	n/a	-0.0025
	(-0.87)		(-0.88)		(-0.83)		(-0.050)
Cash holdings	0.21***	n/a	0.23***	n/a	0.21***	n/a	0.18***
	(3.76)		(5.16)		(4.27)		(3.37)
$\text{Log}(\frac{GDP}{capita})_{region}$	-0.059**	-0.051**			-0.054**	-0.045**	-0.028
	(-2.73)	(-2.65)			(-2.80)	(-2.43)	(-0.17)
Δ GDP_{region}	0.00073	0.0084			0.0014	0.0085	-0.0038
	(0.24)	(1.03)			(0.33)	(1.03)	(-1.14)
$\text{Inflation}_{region}$	-0.35	-0.42			-0.39	-0.50	-0.29
	(-0.88)	(-0.79)			(-0.99)	(-0.96)	(-1.03)
$\text{Flexibility}_{overall}$			-0.0065	n/a	-0.025	n/a	-0.020
			(-0.100)		(-0.40)		(-0.33)
$\text{Flexibility}_{region}$			-0.043	-0.045	-0.042	-0.046*	-0.018
			(-1.63)	(-1.76)	(-1.73)	(-1.87)	(-0.72)
Log(MW)_{region}			0.0043	0.0082*	0.0031	0.0057	-0.0048
			(0.86)	(1.87)	(0.62)	(1.22)	(-0.71)
$\frac{MW_{region}}{MW_{overall}}$			-0.016	-0.050*	-0.0022	-0.024	0.00018
			(-0.63)	(-1.79)	(-0.083)	(-0.81)	(0.0056)
Year-FE	yes	yes	yes	yes	yes	yes	yes
Firm-FE	yes	yes	yes	yes	yes	yes	yes
Firm x Year FE	no	yes	no	yes	no	yes	no
Firm x Market FE	no	no	no	no	no	no	yes
Observations	10,406	8,510	10,439	8,644	9,937	8,108	9,848
Firms	338	149	338	151	336	145	333
R2	0.27	0.26	0.26	0.24	0.27	0.25	0.58

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Table 6 continued

The dependent variable is TOTAL INVESTMENT, which is defined as early-stage 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 abnormal temperature index is constructed as abnormal temperature in a year and region, relative to the base period 1951 to 1980, divided by the interannual standard deviation during the same period. All variables are lagged by one year. T-statistics based on robust standard errors clustered by countries/firms/years 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: In which types of power plants do firms invest?

Panel A: absolute investment levels						
Column	1	2	3	4	5	6
	flexible investment		inflexible investment		renewable investment	
Abn. temp. index	**0.0090****	**0.011*****	**0.00092**	**0.00052**	**0.0018**	**0.0029**
	(2.93)	**(3.14)**	**(0.80)**	**(0.35)**	**(0.58)**	**(0.74)**
Log(assets)	0.0039	n/a	0.014	n/a	0.023**	n/a
	(0.42)		(1.45)		(2.24)	
Profitability	-0.00089	n/a	0.043***	n/a	-0.031	n/a
	(-0.025)		(6.12)		(-0.92)	
Tobins Q	0.014	n/a	0.0096*	n/a	0.0058	n/a
	(1.60)		(1.76)		(1.04)	
Leverage	-0.019	n/a	-0.034	n/a	0.0017	n/a
	(-0.78)		(-0.99)		(0.054)	
Cash holdings	0.11**	n/a	0.032	n/a	0.14**	n/a
	(2.61)		(1.45)		(2.32)	
Log(GDP/capita)$_{HQ}$	0.081**	n/a	-0.052	n/a	-0.099**	n/a
	(2.70)		(-0.65)		(-2.34)	
Year-FE	yes	yes	yes	yes	yes	yes
Firm-FE	yes	yes	yes	yes	yes	yes
Firm x Year FE	no	yes	no	yes	no	yes
Observations	10,876	9,474	10,876	9,474	10,881	9,474
Firms	336	163	336	163	337	163
R2	0.16	0.21	0.37	0.28	0.29	0.25

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Table 7 continued

Panel B: relative investment levels (only investing firms)						
Column	1	2	3	4	5	6
	flexible investment		inflexible investment		renewable investment	
Abn. temp. index	**0.021****	**0.027****	**-0.0038**	**-0.0048**	**-0.013**	**-0.015**
	(2.35)	**(2.62)**	**(-0.58)**	**(-0.64)**	**(-1.25)**	**(-1.15)**
Log(assets)	-0.015	n/a	-0.00039	n/a	0.032*	n/a
	(-0.52)		(-0.019)		(1.81)	
Profitability	-0.0022	n/a	-0.013	n/a	-0.064	n/a
	(-0.027)		(-0.17)		(-0.70)	
Tobins Q	0.011	n/a	0.00055	n/a	-0.016	n/a
	(0.52)		(0.033)		(-0.67)	
Leverage	-0.0070	n/a	0.0092	n/a	0.015	n/a
	(-0.10)		(0.17)		(0.21)	
Cash holdings	0.11	n/a	-0.048	n/a	0.029	n/a
	(0.60)		(-0.83)		(0.19)	
Log(GDP/capita)$_{HQ}$	0.42***	n/a	-0.11	n/a	-0.30***	n/a
	(4.62)		(-1.63)		(-3.01)	
Year-FE	yes	yes	yes	yes	yes	yes
Firm-FE	yes	yes	yes	yes	yes	yes
Firm x Year FE	no	yes	no	yes	no	yes
Observations	4,889	3,616	4,889	3,616	4,897	3,616
Firms	256	120	256	120	257	120
R2	0.40	0.31	0.40	0.097	0.51	0.51

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Table 7 continued

Panel C: change of firms flexibility (run-up time, RuT)				
Column	1	2	3	4
	Δ RuT$_{new-projects}$		Δ RuT$_{new-portfolio}$	
Abn. temp. index	**-0.021****	**-0.058*****	**-0.0036**	**-0.0074***
	(-2.31)	**(-3.00)**	**(-0.87)**	**(-2.03)**
Log(assets)	0.0045	n/a	-0.011	n/a
	(0.057)		(-0.53)	
Profitability	-0.17	n/a	0.066*	n/a
	(-0.57)		(1.85)	
Tobin's Q	0.061	n/a	0.0073	n/a
	(1.46)		(0.73)	
Leverage	-0.11	n/a	-0.014	n/a
	(-0.79)		(-0.31)	
Cash holdings	-0.23	n/a	-0.021	n/a
	(-0.84)		(-0.32)	
Log(GDP/capita)$_{HQ}$	0.38*	n/a	0.089**	n/a
	(2.00)		(2.40)	
Year-FE	yes	yes	yes	yes
Firm-FE	yes	yes	yes	yes
Firm x Year FE	no	yes	no	yes
Observations	3,162	1,766	8,722	7,256
Firms	229	73	314	136
R2	0.33	0.28	0.21	0.18

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Table 7 continued

Gas, gas combined-cycle, and oil power plants are considered as flexible plants. Coal and nuclear power plants are considered as inflexible plants. Run-up time combines the (in)flexibility of all types of plants into one measure; it's defined as average time which is necessary to start-up a power plant in hours. Higher values of run-up time go along with lower flexibility.

Panel A: The dependent variables indicate absolute investments in power plant construction projects. FLEXIBLE investment is defined as early-stage projects to construct 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). INFLEXIBLE and RENEWABLES are defined in the same way.

Panel B: The dependent variables indicate relative investments in power plant construction projects. They are calculated as flexible (inflexible, reneables) power plant projects (in MW) divided by all early-stage power plant construction projects (in MW).

Panel C: The dependent variables indicate the change of the run-up time as measure for inflexibility due to the early stage power plant projects. In columns 1 and 2, the run-up time of early stage plant projects is compared to all existing plants' run-up time in t-1. In columns 3 and 4, the hypothetical run-up time of the new power plant portfolio (including existing and early stage plants) is compared to the existing plants' run-up time in t-1.

Abnormal temperature index is constructed as abnormal temperature in a year and region, relative to the base period 1951 to 1980, divided by the interannual standard deviation during the same period. All variables are lagged by one year. T-statistics based on robust standard errors clustered by countries/firms/years 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: Channel: extreme weather, electricity price volatility, and investments

Panel A: Climate change and weather extremes (region-year analysis)				
Dependent variable: extreme days$_{2.5 std.dev.}$				
Column	1	2	3	4
Abn. temp. index	**0.0059*** **	**0.0052*** **	**0.0046*** **	**0.0046*** **
	(4.82)	**(4.31)**	**(3.32)**	**(3.32)**
Log(GDP/capita)$_{reg}$			0.018	0.020
			(1.03)	(1.24)
Δ GDP$_{region}$				-0.013
				(-0.60)
Inflation$_{region}$				-6.3e-06
				(-0.016)
Year-FE				
Market-FE				
Observations	2,524	2,524	1,996	1,994
Regions	174	174	120	120
R2	0.78	0.79	0.76	0.76
Panel B: Climate change and el. price volatility (region-year analysis)				
Dependent variable: electricity price volatility				
Column	1	2	3	4
Abn. temp. index	**0.025*** **	**0.032** **	**0.033** **	**0.031** **
	(2.77)	**(2.37)**	**(2.37)**	**(2.46)**
Log(GDP/capita)$_{reg}$			1.16*	0.85*
			(1.90)	(1.72)
Δ GDP$_{region}$				2.17*
				(1.96)
Inflation$_{region}$				0.027**
				(2.29)
Year-FE	no	yes	yes	yes
Market-FE	yes	yes	yes	yes
Observations	801	801	774	774
Regions	65	65	62	62
R2	0.76	0.77	0.78	0.78

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Table 8 continued

The dependent variable is EXTREME $\text{DAYS}_{2.5std.dev.}$ in Panel A and EL. PRICE VOLATILITY (which is defined as standard deviation of returns of hourly electricity prices in market m and year t) in Panel B. The analyses are done on the region-year level both Panels because the variables of interest do not vary across firms. T-statistics based on robust standard errors are presented in parentheses. The standard errors are clustered by regions in Panels A and B. ***, ** 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**
General definitions	
Region$_j$	Country or state (for the U.S., Canada, and Australia).
Market$_m$	Wholesale market region for electricity. Typically the market regions equals a country, but the U.S., Canada, and Australia have multiple markets which cover only particular regions (i.e., states). Another exception is Nordpool, which is the common market region for several Northern European countries.
Flexible plant	Gas, gas combined-cycle, and oil power plants are considered as flexible plants.
Inflexible plant	Coal and nuclear power plants are considered as inflexible plants.
Investment planning variables (Source: Own calculations based on WEPP database)	
Total investment$_{i,j,t}$	Early-stage 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 for values > one and to zero if firm i in region j (and year t) has existing production capacity of at least 1 MW but no planned flexible investment.
Flexible investment$_{i,j,t}$	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). The same adjustments as for TOTAL INVESTMENT are made.
Inflexible inv.$_{i,j,t}$	Early-stage inflexible 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). Inflexible power plants are coal and nuclear power plants. The same adjustments as for TOTAL INVESTMENT are made.
Renewable inv.$_{i,j,t}$	Early-stage inflexible 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). Renewables are hydro, wind, and solar power plants. The same adjustments as for TOTAL INVESTMENT are made.
Dummy$_{i,j,t}$	Dummy variable which equals one if total investment is greater than zero and zero if total investment equals zero.
log(MW)$_{i,j,t}$	Natural logarithm of one plus the total capacity of power plant projects of firm i in region j (and year t). Set to zero if firm i in region j (and year t) has existing production capacity of at least 1 MW but no power plant projects. Source: Own calculations based on WEPP database.
# to total$_{i,j,t}$	Number of flexible power plant projects of firm i in region j (and year t), scaled by the number of existing power plants of the same firm i in the same region j (and year t). Set to zero if firm i in region j (and year t) has existing production capacity of at least 1 MW but no power plant projects.

Definition of Variables - continued

Variable	Description
$\log(\#)_{i,j,t}$	Natural logarithm of one plus the number of power plant projects of firm i in region j (and year t). This measure is not scaled. The variable is set to one for values > one and to zero if firm i in region j (and year t) has existing production capacity of at least 1 MW but no power plant projects.
Flexible to total$_{i,j,t}$	Flexible power plant projects (in MW) divided by all early-stage power plant construction projects (in MW) of firm i in region j (and year t).
Inflexible to total$_{i,j,t}$	Inflexible power plant projects (in MW) divided by all early-stage power plant construction projects (in MW) of firm i in region j (and year t).
Renewable to total$_{i,j,t}$	Renewable power plant projects (in MW) divided by all early-stage power plant construction projects (in MW) of firm i in region j (and year t).
Δ RuT$_{new-projects}$	Relative difference in run-up time between early-stage power plant projects of firm i in region j and year t to existing power plants of firm i in region j and year $t-1$. Run-up time is the capacity-weighted average time which is necessary to start-up the power plants in hours. It is based on the production technologies of the firms' power plants. See Reinartz and Schmid (2016) for technology-specific values.
Δ RuT$_{new-portfolio}$	Relative difference in run-up time between the hypothetical new power plant portfolios (consisting of existing plants and early-stage plant projects) of firm i in region j and year t to existing power plants of firm i in region j and year $t-1$. Run-up time is the capacity-weighted average time which is necessary to start-up the power plants in hours. It is based on the production technologies of the firms' power plants. See Reinartz and Schmid (2016) for technology-specific values.
Weather variables (Source: Own calculations based on GHCN data)	
Abnormal temp. index (ATI)$_{j,t}$	Main measure for climate change. The abnormal temperature index in region j and year t is defined as abnormal temperature$_{j,t}$ (see below) divided by the interannual standard deviation during the base period 1951 to 1980 in the same region (see Hansen et al. (1998)). Thus, a value of one indicates that the temperature in this region is one standard deviation higher in the specific year compared to the average temperature during the base period.
Abnormal temp$_{j,t}$	Average temperature in a region j and year t minus the expected temperature in the same region. The expected temperature is calculated as the average temperature in the base period 1951 to 1980 in the same region (see, for instance, Hansen et al. (2012)).
Extreme days$_{2.5 std.dev.}$	Fraction of days in region j and year t which are extreme. A day is defined to be extreme if the average temperature on that day is higher (lower) than the average temperature in the corresponding months during the base period 1951 to 1980 plus (minus) 2.5 times the standard deviation of temperatures during that month in the base period.
Other variables	
Log(assets)$_{i,t}$	Logarithm of total assets [wc02999] in U.S. dollar.
Profitabiltiy$_{i,t}$	Earnings before interest, taxes, depreciation, and amortization (EBITDA) [wc18198] / total assets [wc02999].

Definition of Variables - continued

Variable	Description
Tobin's Q $_{i,t}$	Market capitalization [wc08001] plus total debt [wc03255] divided by book value of common equity [wc03501] plus total debt [wc03255].
$\text{Leverage}_{i,t}$	Total debt [wc03255] / (Total debt [wc03255] + book value of common equity [wc03501]).
$\text{Cash}_{i,t}$	Cash & short term investments [wc02001] / total assets [wc02999].
$\text{Log(GDP/capita)}_{HQ\|i,t}$	Natural logarithm of GDP per capita (in 2010 U.S. dollar) in year t in the headquarter country of firm i. Source: Worldbank.
$\text{Log(GDP/capita)}_{j,t}$	Natural logarithm of GDP per capita (in 2010 U.S. dollar) in region j and year t. Source: Worldbank.
Δ $\text{GDP}_{j,t}$	Change of GDP per capita in region j between year $t-1$ and year t. Source: Worldbank.
$\text{Inflation}_{j,t}$	Inflation rate in region j and year t. Source: Worldbank.
$\text{Flexibility}_{overall}$	Fraction of flexible plants (in MW) of firm i in year t. Source: Own calculations based on WEPP database.
$\text{Flexibility}_{region}$	Fraction of flexible plants (in MW) of firm i in region j and year t. Source: Own calculations based on WEPP database.
Log(MW)_{region}	Natural logarithm of the total capacity of all power plants of firm i in region j and year t. Source: Own calculations based on WEPP database.
$\frac{MW_{region}}{MW_{overall}}$	Fraction of total capacity of power plants of firm i in region j and year t to the total capacity of all power plants of firm i in year t. Source: Own calculations based on WEPP database.
El. Price $\text{Volatility}_{m,t}$	Volatility of electricity prices. Defined as standard deviation of returns of hourly electricity prices in market m and year t. Returns are calculated as differences between hourly prices in U.S. dollar and standardized by the average price in a market.