The Real Effect of Climate Change: Evidence from Investments in New Power Plants

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Abstract

How does climate change affect firms' decisions? One industry which is potentially affected by weather is the electric utility industry. Using a sample of over 10,000 early-stage power plant projects, we estimate the way in which electric utilities adjust their investments and asset structure in response to changes in weather. Our results suggest that energy companies increase their investments on power plants 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. 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] Furthermore, this industry

[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).

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 over 10,000 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 can 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 a huge impact on 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 in order 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 have incentives to adjust their power plant portfolio towards more operational flexibility, e.g., by building more gas-fired power plants which 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. Empirically, these arguments imply that we should observe

[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.

more new power plants in regions in which climate change is more pronounced, especially in flexible and/or renewable generation assets.

Our estimates suggest that firms increase their investments in new power plants in regions in which climate change is more pronounced. This result is based on pooled OLS regressions and models that include firm or firm-year fixed effects. The inclusion of firm-year fixed effects allows us to exploit variation across different regions in which a firm is active. The estimated impact of climate change on investment is considerable. Based on the firm-year fixed effects model, 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 better 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 firms to invest more in flexible production assets (e.g. gas-fired power plants) in regions in which climate change is more severe, both in absolute terms and relative to their total investments. These new plants will tend to increase firms’ overall operating flexibility in these regions.

The reason why firms adjust their production portfolio in this way is related to how climate change affects uncertainty about electricity demand. Theoretically, climate change can lead to less predictable weather and to more extreme weather events, which increase the uncertainty about electricity demand. Consistent with the notion that the climate change induced investment does occur because firms adjust to higher electricity demand uncertainty, we first document that climate change indeed leads to more extreme weather events. For regions with competitive wholesale markets, we then also show that electricity price volatility is higher in regions in which climate change is more severe. This indicates that flexible power plants that can start and stop within short periods of time become relatively more attractive for energy utilities due to the increase in electricity demand uncertainty, which is a consequence of climate change.

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.

These 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 may have implications for other industries as well. Many industries face similar challenges and also require changes to their business models as asset structures. 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 we caution against generalizing our results to other industries because of the unique relation between energy demand and weather, it does seem likely that the real effects of climate change on businesses in many industries are likely to be consequential, and are not well understood at this point.

[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

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 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 sample of energy utilities from all over the world, 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 135 regions (67 countries) and they conduct about 10,000 early-stage power plant construction projects.

2.2. Measuring power plant investments

Data on the single power plants is obtained from the annual versions of the *Platts World Electric Power Plant* database. This comprehensive database contains 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 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.

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[10] 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.

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

Most important for our purposes, this database does not only cover completed power plants, but also 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. Our main dependent 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 which 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 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, not their capacity. For this, 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.

When investigating the channels for changes in the overall level of investments, we also analyze the types of assets in which firms invest. To do so, we distinguish investments in flexible, inflexible, and renewable generation assets. The *Platts WEPP* database contains the technology which is used to generate electricity, so we can classify all plants in broader categories such as coal or gas-fired plants. We classify gas, gas-combined cycle, and oil power plants to be flexible generation assets, coal-fired plants and nuclear plants are to be inflexible, and hydro, wind, and solar plants to be renewable generation assets. We also

[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).

construct firm-level measures which indicate a firm's fraction of existing flexible power plants overall ($\text{FLEXIBILITY}_{\text{overall}}$) or in a region ($\text{FLEXIBILITY}_{\text{region}}$). To aggregate the flexibility of different types of plants into one single number, we also consider how a firms' run-up time as proxy for inflexibility changes due to the early-stage power plant projects (cf. 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 climate 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 each region and year from 1951 to 2015.[13] All temperatures are measured in degrees Celsius. After that, we calculate the average temperature during the base period 1951 to 1980 for each region.[14] We require at least 20 years of non-

[13] We only consider 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.
[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.

missing data on the average temperature during this base period. ABNORMAL TEMPERATURE in a year and region is defined as the difference between the actual temperature and the average temperature during the base period.

To account for the fact that temperatures are generally 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 during our sample period is slightly above one. Overall, these aggregated statistics show that temperatures increased quite substantially on average.

Next, we analyze 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

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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.

[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)

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. This regional heterogeneity will allow us to identify the impact of climate change on investments.

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 and about three percent to investments in inflexible generation. Investments in 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 average run-up time as a proxy for operating inflexibility decreases by about 0.2 due to the new projects. 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. The average temperature

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

index during our sample period is 1.2 and the abnormal temperature about 0.6 degrees Celsius, which indicates a significant temperature increase compared to the base period 1951 to 1980.

3. Estimating the impact of climate change 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, 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 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). Thus, we analyze the investment decisions of all firms in all regions in which they operate.[17] A region is defined as a country or a state (only for the U.S., Canada, and Australia). We use states in these three countries because electricity regulations are taking place on a state-level there.

Our base specification includes year- and firm-fixed effects. Furthermore, we also estimate a specification that contains year x firm-fixed effects. This specification compares investment decisions of the same firm in the same year across different regions. In all specifications, we exploit variation of climate change across time and regions. An alternative would be to also include firm-region fixed effects, but this has the disadvantage that the model then only exploits time-series variation of climate change. Cross-regional differences in climate change, however, are potentially important sources of variation that could affect investment decisions. For this reason, we decided not to use specifications that exploit cross-regional variation of climate change as base models. However, in a robustness test, we also estimate a specification with firm-region fixed effects.

[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.

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

Estimates of this specification are presented 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 climate change is more pronounced. 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 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, this represents a relative increase of 10 to 20 percent. Thus, this effect is not only statistically significant, but also economically relevant. 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 coefficient for leverage and GDP of a firm's headquarter country are negative, but the effect is statistically not significant if firm-fixed effects are added.

3.3. Robustness

Tables 4, 5, and 6 contain estimates of alternative specifications to ensure that the results are not specific to any particular assumptions we make. The first robustness test in Table 4 focuses on the measurement of climate change. In our main analyses, we use the abnormal temperature index (ATI) as proxy for climate change. In Columns 1 and 2 of Table 4, we replace this with the average value of ATI over the past three years. The idea behind this measure is that climate change is a slow process. Thus, the longer-term trend should be more important than one unusually hot or cold year. In addition, we reestimate the equation using the abnormal temperature (not standardized) and its 3-year average in Columns 3-6 of

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

Table 4. Both the statistical significance and the economic magnitude are similar using these alternative specifications.

As a second series of robustness tests, we measure investment in several different ways. Our main measure 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 which 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 by 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 question in which types of power plants 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 may have incentives to adjust their power plant portfolio 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 may increase their investment in renewable generation assets due to public pressure or stricter environmental regulations to reduce CO2 emissions in regions in which climate change is more severe.

Table 7 analyzes this idea empirically. In Panel A, we use total FLEXIBLE, INFLEXIBLE, and RENEWABLE INVESTMENT as dependent variables. They are constructed in the same way as total investment, with the exception that only flexible or inflexible power plant projects are considered. For flexible investment in Columns 1 and 2, we find a strong positive impact of climate change. If we compare the coefficient to the corresponding models for total investment in columns 4 and 5 of Table 2, it turns out that they are of a similar magnitude. This result indicates that the increase in total investments is driven by investments in flexible production assets. In fact, the estimates in Columns 3 to 6 suggest that climate change has no effect on investment in inflexible or renewable production assets.

Second, we look at relative investment levels in Panel B. There we find that the fraction of flexible investments to total investments increases due to climate change. For inflexible and renewable investment, the coefficients are negative but statistically insignificantly different from zero.

Third, we analyze the overall change of the production flexibility of energy utilities in Panel C. For this, we use the run-up time as a measure which aggregates the flexibility of all their power plants into one number. 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 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 the run-up time of the early stage projects is lower than for the existing plants. This result indicates that firms will become more flexible due to their investments. In Columns 3 and 4 we compare the average run-up time of the hypothetical new power plant portfolio (consisting of early-stage projects and existing plants) to that of the existing plants. The results again indicate that the new production portfolios will be more flexible (although the coefficient is negative but statistically insignificant in Column 3).

4.2. How does climate change affect the volatility of electricity demand?

We have documented that changes in climate can have a meaningful impact on firms' investments. 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 importance of this channel, we examine its two underlying hypothesis, that climate change does increase the volatility of demand. Because we cannot observe electricity demand directly, we apply two different test settings. First, we investigate whether climate change leads to more extreme weather events. If there are more extraordinarily hot or cold days, demand for electricity will deviate from normal patterns, which makes flexible generation assets valuable. Second, we rely on 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]

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

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

[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.

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.

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. 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.

We present estimates of these equations in Table 8. The results are consistent with the idea that climate change leads to more extreme weather (Panel A) and more volatility electricity prices (Panel B). They 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. The corresponding number for electricity price volatility is 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. Clearly, and perhaps not surprisingly, 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 over 10,000 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 both the quantity of new power plants that firms build, and the type of power plants they build increases in regions in which climate change is more severe. In particular, 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. Our results imply that a one standard deviation increase in the abnormal temperature leads to a 10 to 20 percent relative increase in investment, suggesting that weather has 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 are 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 way of investing may be very different. Future research is likely to suggest that climate change affects industries in very different but equally important ways.

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Vattenfall's electricity generation in Europe 2014, TWh

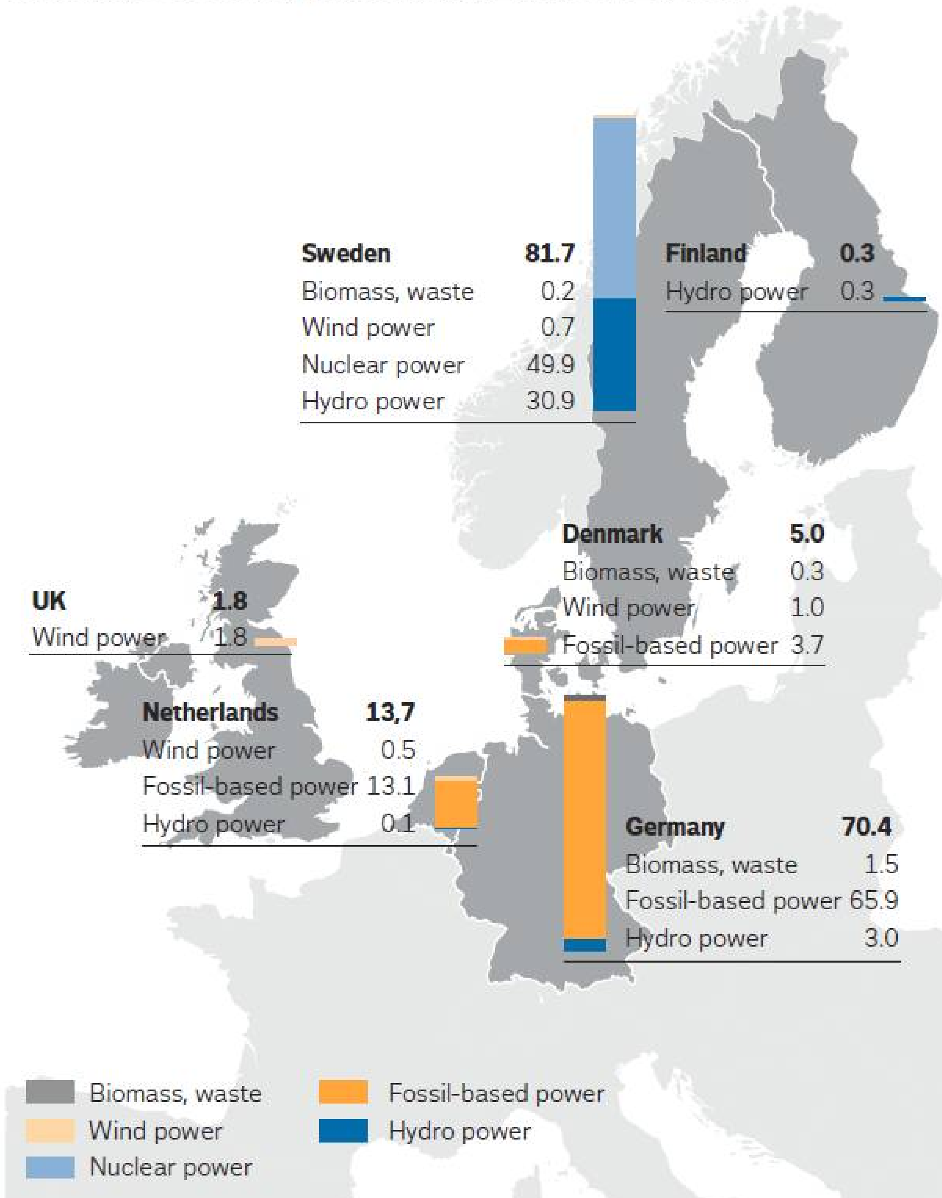
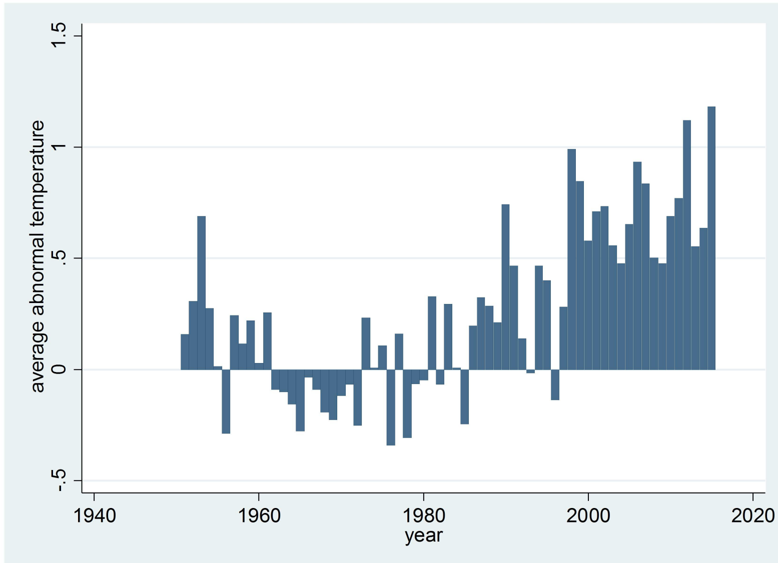
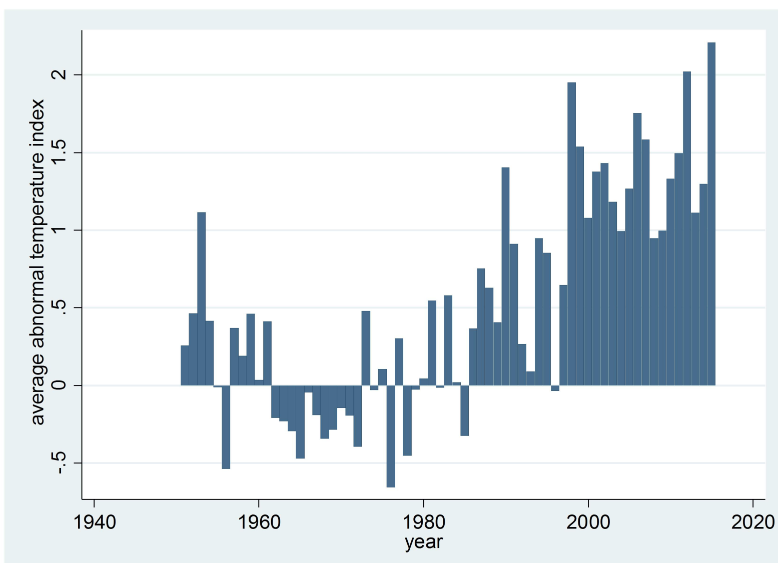


Figure 1: To illustrate our data structure, this figure shows the main countries in which Vattenfall AB owns production capacity (Source: Vattenfall annual report 2014). In our dataset, we would observe Vattenfall's existing production capacity as well as planned new power plants individually for each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

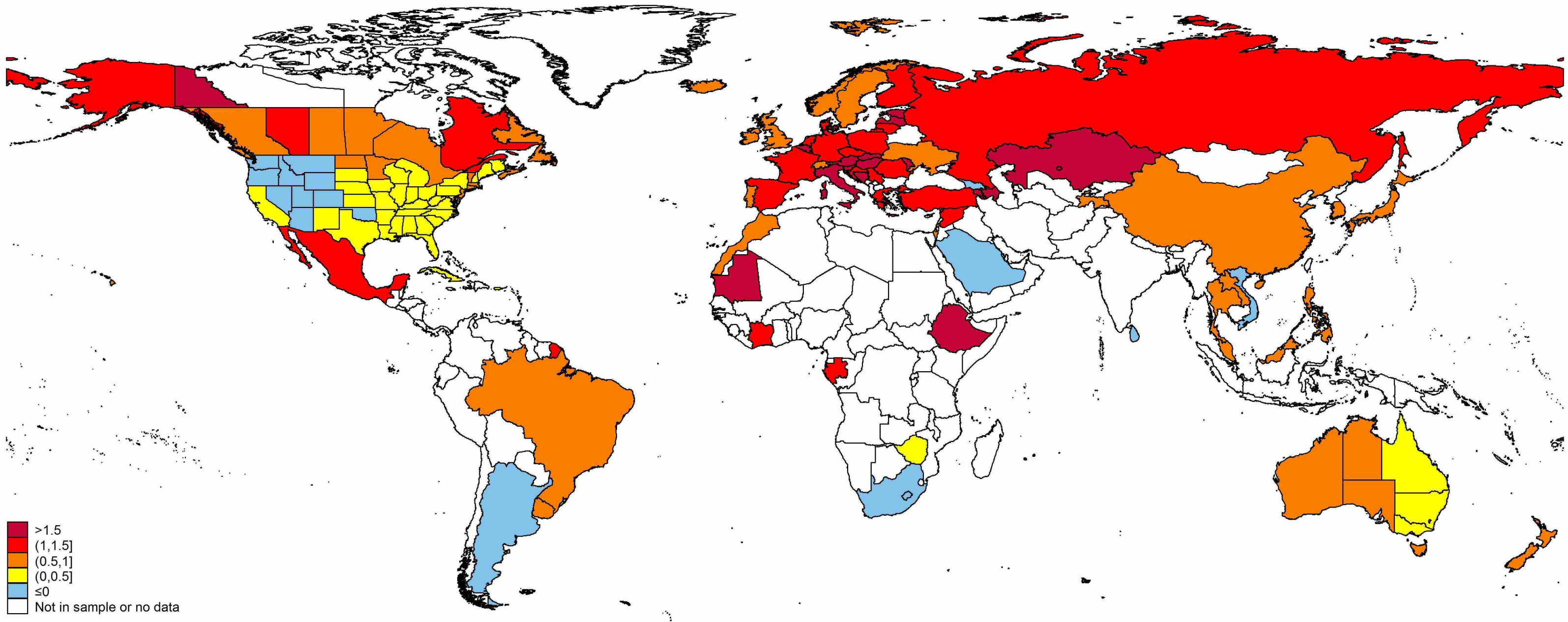


Figure 3: This figure shows the average abnormal temperature during our sample period 2000 to 2015. Abnormal temperature for a region (i.e., country or state for U.S., Canada, and Australia) and year is measured relative to the base period 1951 to 1980. More details about its construction can be found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

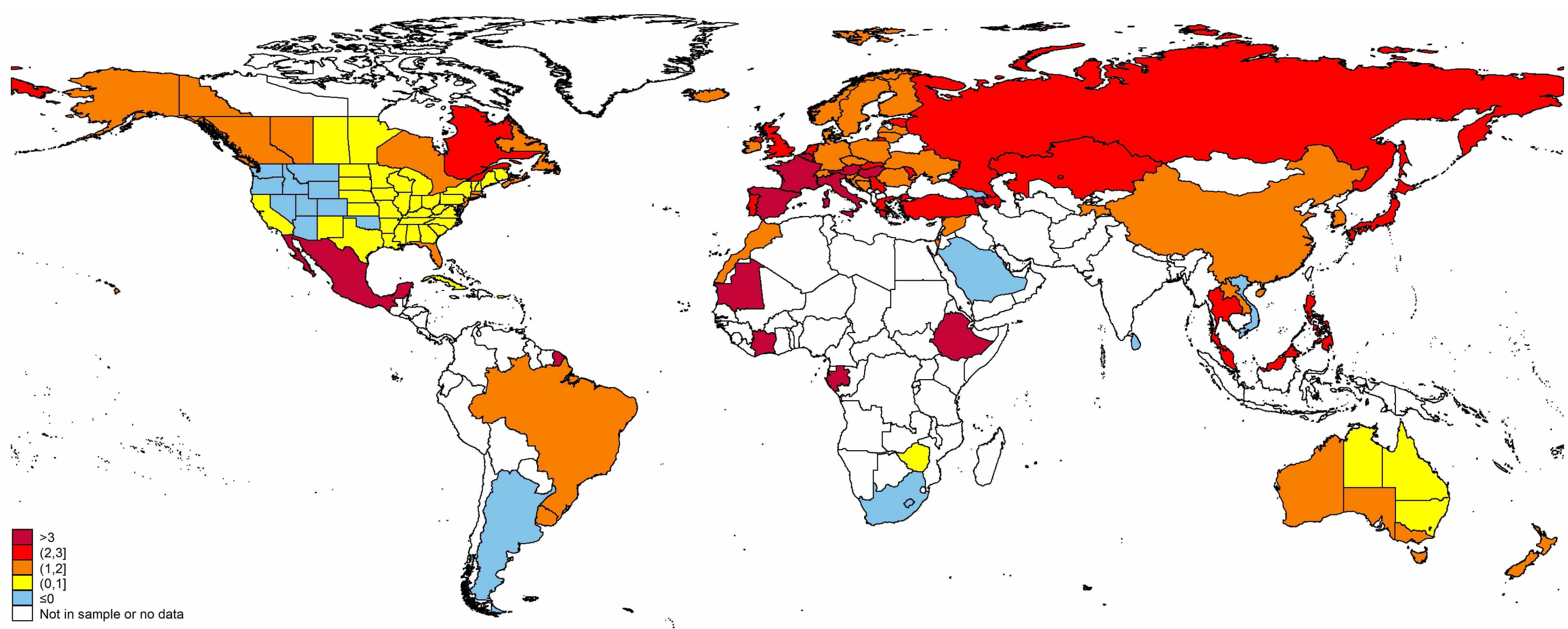


Figure 4: This figure shows the average abnormal temperature index during our sample period 2000 to 2015. The abnormal temperature index is constructed as abnormal temperature divided by the interannual standard deviation during the base period 1951 to 1980 in a region (i.e., country or state for U.S.,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

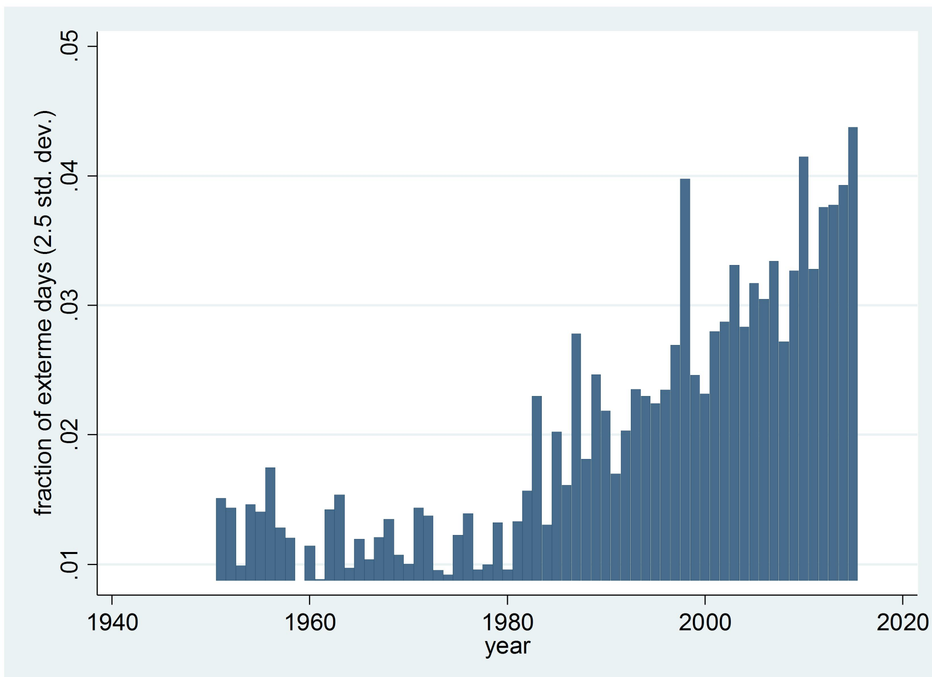


Figure 5: This figure shows the development of the yearly fraction of extreme days over time. A day is defined to be extreme if the average temperature on that day is higher (lower) than the average temperature in the corresponding months during the base period 1951 to 1980 plus (minus) 2.5 times the 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

Technology	**total** **number**	**GW**	**capacity (MW)** **average**	**median**	**countries** **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 RuT$_{new-projects}$	3,400	-0.23	-0.92	-0.39	0.19	0.72
Δ 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 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
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
ATI$_{3y}$	**0.014*** **	**0.014*** **				
	(3.13)	**(3.51)**				
Temp. index			**0.023*** **	**0.031*** **		
			(3.63)	**(4.63)**		
Temp. 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)
$\Delta\ \text{GDP}_{region}$	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 $\text{days}_{2.5std.dev.}$				
Column	1	2	3	4
Abn. temp. index	**0.0059*** **	**0.0052*** **	**0.0046*** **	**0.0046*** **
	(4.82)	**(4.31)**	**(3.32)**	**(3.32)**
$\text{Log(GDP/capita)}_{reg}$			0.018	0.020
			(1.03)	(1.24)
Δ GDP_{region}				-0.013
				(-0.60)
$\text{Inflation}_{region}$				-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)**
$\text{Log(GDP/capita)}_{reg}$			1.16*	0.85*
			(1.90)	(1.72)
Δ GDP_{region}				2.17*
				(1.96)
$\text{Inflation}_{region}$				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 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.