Drought and Investment in Electricity Markets

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Abstract

Worsening drought under climate change may pose a threat to electricity markets, since thermal electricity generation can be an extremely water intensive process. Endogenous changes in the types of technologies used to generate electricity may mitigate this threat, but this adaptation is largely overlooked in the existing literature. This paper studies the impact of drought on electricity markets accounting for both the direct impact on production and the indirect effect through technological adaptation. To estimate the production effect, I exploit temporal variation in drought conditions to show that drought shocks shift generation away from high water use thermal plants, and are associated with up to a 30% increase in wholesale prices. To incorporate technological adaptation, I estimate a model of investment and production in the Texas electricity market, which is novel in incorporating drought as a determinant of production costs. I apply counterfactual climate change scenarios to the model and find that worse future drought decreases investment in high water use plants by up to 20%, and increases investment in higher emissions, dry cooled plants. The findings in this paper highlight the importance of accounting for endogenous changes to the grid, both with respect to optimal policy implementation and measuring grid emissions.

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1 Introduction

Climate change exacerbates drought conditions, making drought events both more frequent and more severe (USGS, 2023). Droughts in North Carolina (2007), Texas (2011), and France (2022) have shown that this is potentially a threat to electricity markets, since thermal electricity generation (such as from coal and natural gas) can be an extremely water intensive process (Averyt et al., 2011).[1] In the short run, drought shocks may reduce production from high water use thermal plants, with other, less efficient, plants increasing production to substitute. In the long run, depending on investment costs, firms may adapt to increased drought by shifting away from water intensive plants and instead investing in more water efficient technologies. These drought-driven changes in the set of generating technologies could in turn translate into changes in wholesale energy prices, grid reliability, and overall emissions.

Understanding the risk posed by climate change-induced drought requires estimating the direct, short-run effect of drought on production as well as the endogenous changes in the mix of generating technologies. However, existing work in this area has focused almost exclusively on the former, using either retrospective analyses of drought given the historic technology mix or detailed climate simulations with assumed, exogenous technology mixtures. By omitting adaptation of the technology mix, these existing studies have limited external validity with respect to projecting future climate impacts.

This paper fills this gap in the literature by estimating the impact of drought on electricity markets, accounting for both the direct impact on production and adaptive changes in the technology mix. I start by showing that drought reduces generation from high water use plants, with the lost generation being replaced by more costly, less water intensive plants. I then document potential investment-based adaptation: investment in high water use plants is negatively related to worse historic drought conditions. Lastly, I use these historic relationships between electricity production and drought to microfound an empirical model used to simulate electricity production under counterfactual future climate scenarios. The model is unique in incorporating drought as a production input, which results in the equilibrium

[1] In the U.S. about 80% of total electricity generation comes from thermal generators (EIA, 2024).

technology mix being endogenous to future drought conditions. The counterfactual analyses predict that under more severe future drought conditions the equilibrium technology mix reduces investment in high water use plants by up to 20%, and increases investment in less efficient, dry cooled thermal plants. I find that this shift in investment does little to offset the impact of drought shocks on prices.

I first estimate the direct impact of drought shocks on thermal production in the spot market, expanding on existing work by considering both the drought conditions where the plant is located, as well as the market wide drought conditions (Eyer and Wichman, 2018; Mamkhezri and Torell, 2022; Qiu et al., 2023).[2] For this analysis I use panel data on drought conditions and plant level production and prices in Texas. I find that firsthand exposure to a worse drought shock reduces generation from high water use plants, while dry cooled plants increase generation in response to worse market wide drought. This finding highlights the importance of market equilibrium in determining the drought effect. The drought-driven changes in generation are associated with a significant increase in wholesale energy prices, with a novel finding that there are larger price effects during non-peak hours when quantity demanded is low (McDermott and Nilsen, 2014). This finding is indicative that the available technology mix is important for determining the price effect.

I then exploit the temporal variation in long run drought trends to document that plant investment pushes the technology mix towards dry and non-thermal plants after periods with worse average drought conditions. To the best of my knowledge, there is no other quantitative evidence documenting the relationship between power plant investment and drought. With respect to understanding the impact of climate change, this result suggests that it is not prudent to extrapolate from the estimated production effects, since the exposed set of technologies is related to long term drought conditions. To explicitly accommodate endogenous adaptation of the technology mix for counterfactual analyses of drought conditions under climate change, I combine the reduced form results into a structural model.

[2] Focusing on Texas allows me to estimate the direct impact of drought on thermal generation since there is negligible hydroelectric generation in this market. Some existing work which also examines drought at the plant's location versus drought elsewhere in the market has found increases in thermal generation due to drought shocks in contexts with significant hydroelectric generation, likely due to thermal plants increasing production to offset the lost hydroelectric generation (Eyer and Wichman, 2018; Qiu et al., 2023). To the best of my knowledge there is no other research looking at both plant level and market wide drought in a context without hydroelectric generation.

I develop a model of investment and production where plants make a one time investment in generating capacity, then produce electricity in response to an equilibrium wholesale price in a repeated competitive market. Each plant is assigned both a location they can enter into and a technology type, which jointly determine the plant's investment costs, operating costs, water needs and drought exposure. Plants first choose how much capacity to build to maximize their expected sum of discounted profits, less the associated investment costs. They then produce electricity each period, subject to location specific environmental shocks and the capacity constraint determined by the investment decision. Non-thermal plants produce electricity based on exogenously determined productivity draws, reflecting the dependence of these plants' production on natural factors like sunshine and wind. Thermal firms instead choose their optimal production taking prices as given. The equilibrium objects of interest are the resultant technology mix and wholesale energy prices. My model augments similar models of electricity markets (Elliott, 2022; Reguant, 2014) by incorporating drought conditions as a determinant of production costs.

I estimate the model working backwards in two steps, first estimating the plants' production costs then estimating the investment costs. For production costs, I invert the plants' first order conditions and solve for the cost parameters using a Tobit specification to accommodate censoring arising from the capacity constraints. The parameter estimates align with the motivating analyses, with average costs increasing by up to \$35/MWh for high water use plants during extreme drought conditions, but no meaningful change in production costs for other thermal plants. For investment costs, I again use the plants' first order condition to solve for optimal capacity investment as a function of the plants' expected future marginal profit flows. To estimate expected future marginal profits I assume that plants have rational expectations over future prices conditional on the realized state variables and previous prices, and that they believe prices are unresponsive to their decisions.

To simulate the impact of climate change-driven drought on electricity supply, I combine my estimated model with drought predictions from standard climate change models (Zhao and Dai, 2022). I use drought distributions for 2070–2099 under two alternative climate change scenarios with different drought severity forecasts: low-to-moderate and high. I find that relative to the baseline technology mix (without changes in drought conditions), there are shifts in investment away from high water use and towards dry cooled plants. For the high drought severity scenario, the amount of high water use capacity declines 20% (1,381 MW) from baseline. With respect to prices, I find that endogenous adaptation does little to offset the drought effect. Beyond the direct impacts on the market, the change in the technology mix due to drought raises concerns about changes in plant externalities. Since dry cooled plants are relatively dirty, a back of the envelope calculation shows that the technology mix shift is associated with a 7% increase in grid emissions under the high drought scenario.

The results from the analyses in this paper have important implications for grid stability, end consumer prices, and energy policy. Adaptive investment shifts capacity away from high water use thermals and towards dry cooled technologies. Considering this endogenous change is important for designing policies surrounding investment in non-thermal technologies that account for changed future energy prices and returns to non-thermal plants. Additionally, the spatial distribution in growth of emissions is important to consider from an environmental justice lens.

This paper contributes to the literature on the consequences of climate change by providing the first analysis that accounts for endogenous technological adaptation when estimating the impact of drought on electricity generation.[3] Within this literature, there is a subset of existing work using retrospective analyses to estimate the impact of historic drought shocks with an exposed, fixed set of plants (Scanlon, Duncan, and Reedy, 2013; Herrera-Estrada et al., 2018). Extrapolation of these results potentially understates the impact of climate change driven drought, since plants in areas exposed to more drought may have already taken adaptive measures. Alternatively, another subset of literature uses climate model simulations relying on assumptions about what the future generating mix will be that abstract from drought (Poch, Conzelmann, and Veselka, 2009; Koch and Vögele, 2009; Harto and Yan, 2011). This approach may overstate the climate change impact by assuming

[3]Existing work has shown climate change is already impacting people around the world in almost every facet of life, including food security (Deschênes and Greenstone, 2007; Burke and Emerick, 2016), natural disasters (Botzen, Deschênes, and Sanders, 2019; Desmet et al., 2021), and heat-related mortality (Deschênes and Greenstone, 2011; White, 2017). With respect to energy, most of the existing work is focused on demand side changes (Cline, 1992; Aroonruengsawat and Auffhammer, 2011; Auffhammer, Baylis, and Hausman, 2017).

the generating technologies do not adapt to changes in drought. My analysis bridges these existing works by providing novel evidence that drought results in technological adaptation, and new quantification of the supply side impact of climate change explicitly accommodating this endogenous investment.

This paper also builds on existing models of firm investment decisions, in particular with spatially distributed costs or restrictions. The existing work in this area is largely focused on the impact of industrial policy and environmental regulations in determining investment across many industries (Gowrisankaran and Town, 1997; Ryan, 2012; Fowlie, Reguant, and Ryan, 2016). For electricity markets in particular, significant consideration has been given to understanding how spatial characteristics and policies influence investment in alternative generation technologies (Fell and Linn, 2013; Butters, Dorsey, and Gowrisankaran, 2021). However, to the best of my knowledge none other than my paper consider the potential role of environmental characteristics or climate change in determining investment.[4]

The remainder of the paper is structured as follows. Section 2 provides background information on generation technologies and the market and Section 3 details the data used. Sections 4 and 5 present reduced form evidence on the relationship between drought and electricity markets, while Section 6 incorporates these relationships into a structural model, estimated in Section 7. Section 8 uses the model to run counterfactual analyses and Section 9 concludes.

2 Generation Technologies and ERCOT Overview

2.1 ERCOT Market Structure Overview

The analyses focus on the Electricity Reliability Council of Texas (ERCOT), which has several features making it an attractive setting. First, ERCOT is a large market both in terms of transaction volume and spatial area, serving 26 million consumers across Texas. Second, it is isolated from other grids, limiting the impact of imports or shocks to systems

[4]Chen, Fu, and Chang (2021) most closely fill this gap using reduced form analyses to examine the relationship between installed capacities of wind and solar as a function of greenhouse gas emissions, extreme temperatures, and extreme weather events.

outside of Texas.[5] Third, within ERCOT there is negligible hydroelectric generation, ruling out indirect effects of drought on thermal generation through equilibrium impacts due to changes in hydroelectric generation.[6] Lastly, ERCOT was restructured in 1999, and while there is some evidence of strategic behavior in this market, it is largely considered to be competitive (ERCOT IMM, 2023; Woerman, 2023).[7]

The market operates through an auction framework, with the end result that power plants sell electricity to the grid and receive a common price, which is determined by the operating costs of the marginal plant that fills demand. The auction structure also results in plants operating in order of least cost. This means that in periods of low (high) demand, the marginal plant is relatively low (high) cost leading to a lower (higher) wholesale price.[8] More detailed information on the market structure is available in Appendix Section A.1.

2.2 Comparison of Alternative Generation Technologies

Power plants rely on different types of technologies to generate electricity, which are subject to trade-offs between their ability to respond to changes in demand, efficiency[9], and water needs. Non-thermal technologies, such as wind and photovoltaic generators, produce energy subject to environmental conditions and are generally considered non-responsive to demand. Thermal technologies on the other hand produce electricity by burning fuel, allowing them to be more responsive to demand. Within thermal generators, there is variation in demand response and efficiency, with the most demand responsive technologies generally also having moderately lower efficiency (EIA, 2023; Joshi et al., 2020).

How a thermal plant is cooled determines the plant's water needs and impacts the plant's efficiency. High water use plants pull cooling water from a nearby source and then return the now warmer water back to the source. By pulling cold water each time, the plant uses minimal energy for cooling but requires a significant amount of water. In contrast, low

[5]There are only 5 interconnection points with other grids, which can contribute less than 1% of total capacity.

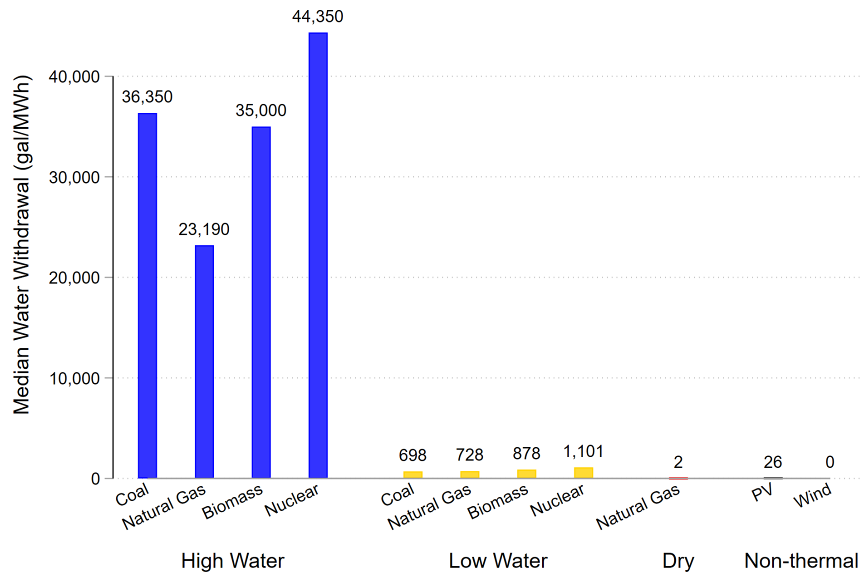
[6]Hydroelectric accounted for less than 0.1% of total generation in 2022.

[7]The Herfindahl-Hirshman index of concentration was 187 in 2022.

[8]An important caveat to this framework is that in actuality there can be location specific prices resulting from transmission constraints, leading to some cross-sectional variation in prices. Between January 2011 and January 2024, 75% of hourly location specific prices were within 5% of the market wide average price.

[9]Measured as the amount of energy required to produce one kWh of electricity.

Figure 1: Water Withdrawals by Technology



Note Figure plots the median volume of water withdrawn per MWh of electricity produced. Technologies are disaggregated along the x-axis, first by cooling and then by fuel type. Values are collected from Macknick et al. (2011).

water use plants reuse the cooling water, reducing water needs but also reducing a plant's efficiency by 2-5% (World Nuclear Association, 2020). Lastly, plants may be cooled without water (dry) but face larger reductions in efficiency (EPRI and Commission, 2002). Figure 1 shows that the differences in water needs, as measured by withdrawals, across technologies are significant.[10] More detailed information on generation technologies is available in Appendix Section A.2.

3 Data

I combine data from several sources to create a monthly panel covering power plants across the US from 2001 to 2023. The data consist of three key parts: power plant characteristics, drought conditions, and, for the subset of plants in ERCOT, spot market data. These are detailed further in the subsections below. Additional data sources and details are in

[10]For this project, I focus on variations in water withdrawals rather than water consumption. Since the analysis is focused on how drought impacts the amount of water available to a plant, I focus on withdrawals as being the relevant metric.

Appendix Section B.

3.1 Plant Characteristics

Data on power plant locations and characteristics are from the US Energy Information Administration (EIA), form 860. This data covers all plants with at least 1 MW of generating capacity across the US since 2001. For each plant, I observe the plant's location coordinates, total production (nameplate) capacity, modal fuel type, and the year and month that the plant was first operational and retired, if applicable. I define thermal plants as those that primarily use coal, natural gas, or petroleum for fuel and non-thermal plants as those that primarily use wind or solar.[11] I also observe the plant level cooling system since 2009 for plants over 100 MW which I use to classify thermal plants into three water use categories: high, low, and dry. Due to data limitations, I drop plants with multiple cooling technologies from my sample and assume that plants had the same technologies pre-2009 as they do post-2009.[12]

Characteristics of the plant sample for both the US and ERCOT are presented in Table 1. In both markets, high and low water use plants have significantly larger capacities than dry and non-thermal plants, so that even though there are less of these plants they make up a significant share of generation and capacity. In ERCOT, non-thermals play a larger role compared to the US average, while high water use plants produce relatively little.

3.2 Drought Data

Drought and monthly total precipitation data are collected from the National Atmospheric and Oceanic Administration's (NOAA) Climate Division Dataset (Voase et al., 2014). I define drought using the Palmer Hydrologic Drought Index (PHDI) which measures hydrologic drought (ie. changes in stream flows or reservoir levels) on a scale of -10 to 10, with positive

[11] Nuclear is omitted from my categorization of thermal generators because nuclear plants have unique operating features that make them distinct from the other thermal plants. I also exclude hydroelectric plants.

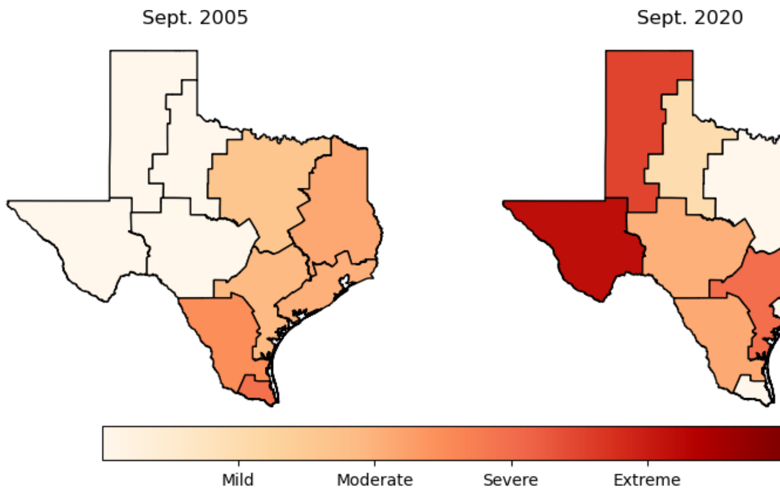
[12] Of the 1,098 thermal plants for which I observe cooling information, 11% are observed with more than one type of operating cooling system.

Table 1: Power Plant Characteristics

	Non-thermal	High Water	Low Water	Dry
Panel A: US Aggregate Statistics				
Number of plants	7,200	295	522	3,030
Percent of total capacity	21	16	38	25
	(0.44)	(0.25)	(0.23)	(0.06)
Percent of total generation	22	13	54	11
	(4.56)	(1.03)	(3.33)	(1.44)
Panel B: US Plant Statistics				
Operating year	2016.12	1958.81	1987.69	1991.77
	(5.87)	(11.90)	(20.68)	(22.18)
Age at retirement	19.67	59.23	43.55	30.14
	(10.59)	(11.17)	(15.10)	(20.64)
Mean capacity (MW)	32.55	589.74	796.12	88.75
	(73.03)	(753.98)	(710.43)	(227.43)
Mean generation (GWh)	7.81	144.29	274.79	11.76
	(19.01)	(224.21)	(248.12)	(55.35)
Panel C: ERCOT Aggregate Statistics				
Number of plants	380	27	77	259
Percent of total capacity	37	12	39	13
	(0.88)	(0.25)	(0.66)	(0.06)
Percent of total generation	36	4	50	10
	(8.10)	(1.09)	(6.21)	(1.37)
Panel D: ERCOT Plant Statistics				
Operating year	2015.47	1963.52	1986.00	2009.00
	(5.97)	(12.94)	(20.31)	(17.36)
Age at retirement	12.25	44.80	45.46	26.07
	(3.19)	(9.70)	(14.21)	(17.90)
Mean capacity (MW)	130.41	580.34	674.44	67.61
	(118.31)	(572.99)	(451.22)	(194.70)
Mean generation (GWh)	35.31	77.61	246.89	16.07
	(35.95)	(93.82)	(180.17)	(65.12)
Non-zero generation indicator	0.97	0.76	0.97	0.96
	(0.17)	(0.44)	(0.17)	(0.19)

Note Table presents descriptive statistics for power plants in the US (Panels A and B) that were operational at any point since 2000 and additional statistics for the subset of power plants located in ERCOT (Panels C and D). Data is from January to December 2022. Standard deviations, shown in parentheses, are taken over both plants and time.

Figure 2: Map of Average Drought



Note Figure maps PHDI index values for NOAA climate divisions in Texas for September of 2005 and 2020. Hash marks denote the beginning of drought severity category defined by NOAA.

numbers reflecting more severe drought and 0 indicating normal conditions.[13] Measuring hydrologic drought in this setting is important since it better reflects the water supplies that are actually available to power plants, compared to simply precipitation or shorter term drought measures.

The PHDI is measured and normalized at the climate division level, where climate divisions are climatically similar areas within the US defined by NOAA (Voase et al., 2014). The normalization process means that drought is interpreted as a deviation away from the climate division's average water availability. Because of this feature of the drought measure, identification for the subsequent analyses stems from cross sectional and temporal differences in the *deviation* of conditions from local normal conditions. Figure 2 presents a visual example of this variation.

3.3 Market Data

The spot market data combines monthly plant level net generation from EIA-923 with ERCOT market demand and prices.[14] For demand, I aggregate hourly data to a monthly measure of market wide load (total quantity delivered). Market average and location specific

[13] I scale the raw PHDI data by -1 to make worse drought a more positive number for ease of interpretation.
[14] I drop February 2021 due to an extreme winter storm which resulted in outlier market data.

prices are available in 15 minute intervals since 2010, which I average over time to construct both average and location-specific monthly prices.[15] I also construct peak and non-peak period prices for each month by averaging the 15 minute prices over the peak (2pm to 9pm) and non-peak (9pm to 2pm) hours of demand, respectively.[16]

4 Empirical Evidence on Spot Market Outcomes

This section uses data on plant production, prices, and drought to estimate the effect of a drought shock on electricity production. I first show that direct exposure to drought reduces generation from high water use plants, while worse market wide drought increases generation from dry plants. This result captures both the direct impact of drought on plant production as well as the indirect effect working through changes in the market equilibrium, with dry plants substituting for high water use plants. I then show that worse market wide drought shocks lead to substantially higher wholesale prices, with consistently larger effects during non-peak hours. In combination with the first result, this heterogeneity reflects the importance of the substitute set of generators in determining the total price effect of a drought shock.

4.1 Methodology

I regress measures of production and price on two measures of drought. I measure drought at the plant's location, $\text{Drought}_{l,t}$, using the PHDI value of month t for the climate division l where the plant is located. I also include the average drought elsewhere in the market, $\overline{\text{Drought}}_{-l,t}$, which is the average of the PHDI values in month t across the nine other climate divisions in Texas. I use standard cutoff PHDI values to categorize both drought measures into five bins: no drought, mild, moderate, severe, and extreme.[17] I use categorical measures of drought to allow for non-linearities in the production response. Note that $\overline{\text{Drought}}_{-l,t}$

[15] I use prices from the day-ahead market. By location specific prices I mean the hub-level prices, detailed in Appendix Section A.1.

[16] The hours used to define the cut-offs for peak and non-peak hours are from the ERCOT load data and reflect the boundaries for above and below the top tercile of average hourly demand.

[17] I drop observations where the PHDI is less than -4, since extreme wetness could be indicative of other environmental shocks that could impact generation (ie. hurricanes or flooding).

mechanically reflects much more severe total drought than $\text{Drought}_{l,t}$, since for $\overline{\text{Drought}}_{-l,t}$ to be classified as severe the average of the index across nine climate divisions must be sufficiently high, whereas $\text{Drought}_{l,t}$ relies only on conditions in one climate division.

For the sample of operating, utility owned plants in ERCOT, I estimate the following specification for plant i in location l in period t:

$$y_{i,t} = g\Big(\sum_{z \in Z} \alpha_z \text{Drought}_{l,t} + \sum_{z \in Z} \beta_z \overline{\text{Drought}}_{-l,t} + \Gamma X_{i,t} + \phi_l + \phi_{m(t)} + \varepsilon_{i,t}\Big) \tag{1}$$

The vector of covariates $X_{i,t}$ always includes a market level linear year trend and quadratic in local temperature. For generation outcomes, $X_{i,t}$ also includes the location level price for the plant, instrumented for by total ERCOT load, while for price outcomes $X_{i,t}$ includes the natural log of total ERCOT load. I also include month-of-year, $\phi_{m(t)}$, and climate division, ϕ_l, fixed effects to account for seasonality in production and unobserved regional characteristics such as operating expenses or non-market production needs.[18] Standard errors are clustered at the level of spatial variation in the drought measure, which is the climate division level. For price outcomes I also cluster at the month-of-sample level to account for cross-sectional correlation in the error terms arising from assigning location level prices to plants.

For generation outcomes, I use two measures of production $y_{i,t}$ to understand the intensive and extensive changes in generation across technologies. For the intensive margin, $y_{i,t}$ is the share of capacity used measured as the total amount of energy generated (MWh) divided by the plant capacity (MWh). Because plants cannot produce negative energy or above capacity, even if it would be optimal to do so, the observed amount of energy produced is a censored measure of the true optimal amount of energy generation. Because of this censoring, when using the share of capacity used as the outcome of interest, the function $g(\cdot)$ in Equation 1 reflects the mapping from the linear regression specification to a tobit model, with censoring at values zero and one. For the extensive margin, $y_{i,t}$ is an indicator for positive net generation (ie. plant is running).[19] The unconditional probability that a

[18] I use climate division fixed effects instead of plant level so that the reported marginal effects are consistent (Chamberlain, 1980).

[19] Due to the energy demands associated with turning generators on and off, in the data there are plants with negative net generation in a month. As a simplification I replace negative net generation values with zero.

given plant is running is generally quite high (eg. 75% for high water use, 93% for low water use), so $g(\cdot)$ for this outcome is defined as the cumulative distribution function of a standard normal to map Equation 1 to a probit model. I estimate Equation 1 separately for each of the four technology types to allow for greater flexibility in the relationship between the covariates and production outcome measures.

For price outcomes, I focus on the average price, the average peak price, and the average non-peak price using the location level prices. I use the natural log of these average prices as the outcome variable to allow for interpretation of the coefficients of interest as a percent change. I estimate Equation 1 only once, combining all technology types, since each firm is a price taker and as such price received should not vary by technology type, conditional on operating.

4.2 Identification

Interpreting $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ as the causal effect of drought conditions on plant production through cooling water supplies requires the assumptions that drought is conditionally exogenous and only impacts production through cooling. Given the stochastic nature of drought shocks the first assumption seems generally reasonable. However, through failures of the second assumption the exogeneity assumption may also fail.

First, drought could be related to shifts in the demand curve for example by increasing electricity use for irrigation or by increasing air conditioning use through a positive correlation with temperature (Hoerling, 2018). These correlated demand shifters would act as confounders for estimating the supply side shocks by impacting both prices and production. To account for this potential confounding, I control for the quantity demanded in the price regressions and average wholesale energy prices in the production specification. Note that since generation may influence prices through unobserved, aggregate shocks, I instrument for price with load which is standard in the literature (Bushnell, Mansur, and Saravia, 2008). This instrument is valid since short-run electricity demand is generally considered price inelastic. A more thorough discussion on this is presented later in Section 6.3.2.

Second, there could be confounding from additional drought-related supply shifters, most notably natural gas prices. Natural gas is increasingly mined through water intensive hydraulic fracturing methods, often in Texas, so that drought could simultaneously affect thermal plants' fuel costs in addition to cooling water supplies (Stevens and Torell, 2018). This dynamic may result in upward bias of effect magnitude, since the returned estimates would jointly capture the direct drought effect and a fuel cost effect, and is not easily solved. Because ERCOT is a large consumer of natural gas, changes in ERCOT generation could influence natural gas prices so that controlling for fuel prices would implicitly control away the effect of interest.[20] While I am unable to fully eliminate this source of bias, comparison of the estimated effects across technology types should be relatively unbiased since all technology types rely heavily on natural gas and therefore subject to the same input price shock.

4.3 Results

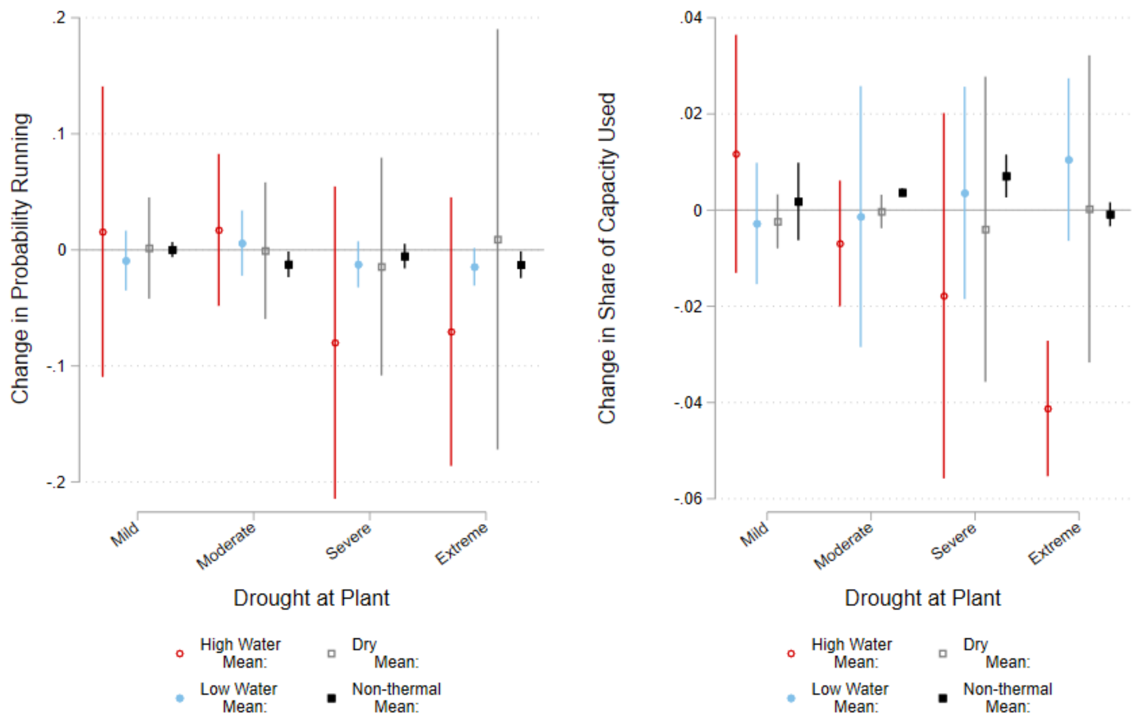
4.3.1 Generation

Local drought conditions reduce generation from high water use plants but have negligible impact on generation from other technologies. As shown in Figure 3, while there is no significant change for the probability a plant is generating (left panel), the marginal effect estimated for generation as a share of capacity is steadily decreasing with drought severity for high water use plants (right panel). Conditional on the average drought outside of a plant's climate division, entering into severe drought reduces the share of capacity used by high water use plants by 3.3 percentage points relative to non-drought conditions, conditional on non-zero generation. The average share of capacity used by high water use plants when generating is 17%, making the 3.3 percentage point reduction an economically significant 19% decrease. For the other technology types, the marginal effect estimates for both the intensive and extensive production margins are fairly stable across drought conditions, reflecting a limited drought effect. These findings show that direct drought exposure is costly for high water use plants but not for less water intensive plants.

Average drought conditions everywhere else in the market instead appear to affect only dry cooled plants, increasing both the probability of generating and the average share of capacity used to generate. As shown in Figure 4, the marginal effect estimates are generally

[20]Natural gas used for electricity generation in Texas accounted for about 15% of the national total of natural gas used for electric power in 2023 (EIA, n.d.).

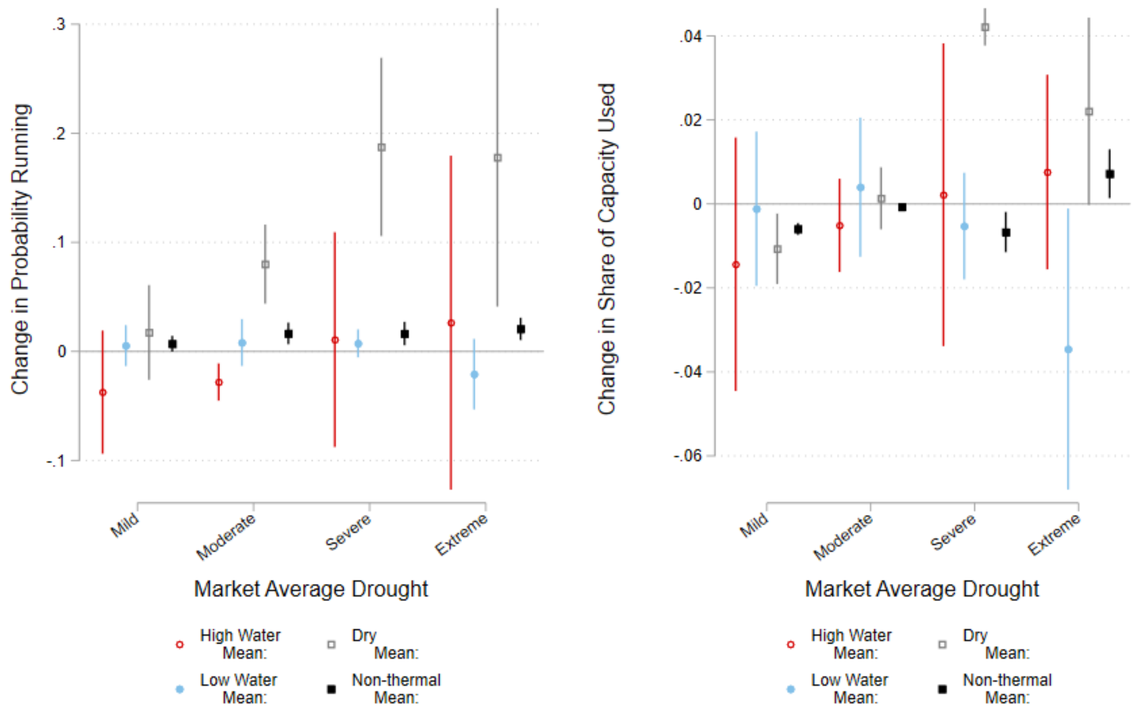
Figure 3: Effect of Drought at Plant Location



Note Figure plots marginal effect estimates for the impact of drought at the plant's location on the probability the plant has non-zero generation (left panel) and the share of capacity used for generation (right panel). The analysis is run separately for each of the four technology groups shown in the legend. Non-drought conditions are the omitted category. Standard errors are clustered at the plant level. 95% confidence intervals are denoted by the vertical bars.

increasing with drought severity for both generation outcomes for dry plants. Conditional on the drought inside of a plant's climate division, entering into severe average drought everywhere else in the market increases the probability a dry plant is running by 1.8 percentage points and the share of capacity used by 1.8 percentage points, relative to average non-drought conditions. The average share of capacity used by dry plants when producing is 38%, making a 2.5 percentage point increase a 7% increase. The marginal effect estimates for the other technologies are again fairly stable across drought severity. It is worth noting that there are small but statistically insignificant increases in the probability that non-thermals are running, a result which could be spurious or may reflect optimizing behavior from non-thermal plants (eg. timing of planned outages). Overall, these results suggests that in response to market equilibrium changes arising from the adverse impacts of drought

Figure 4: Effect of Average Drought Elsewhere



Note Figure plots marginal effect estimates for the impact of average drought elsewhere in the market on the probability the plant has non-zero generation (left panel) and the share of capacity used for generation (right panel). The analysis is run separately for each of the four technology groups shown in the legend. Non-drought conditions are the omitted category. Standard errors are clustered at the plant level. 95% confidence intervals are denoted by the vertical bars.

on high water use plants, dry cooled plants increase production to substitute for the affected high water use generation.

The results from this analysis roughly align with results from similar analyses in existing work. For example, both Eyer and Wichman (2018) and Mamkhezri and Torell (2022) find relative increases in generation from dry cooled plants during drought conditions in Texas over similar time frames. While direct comparison of estimates is difficult, since these papers only consider local drought conditions, in general my coefficient estimates are significantly smaller in magnitude than theirs. Other analyses looking beyond Texas but following similar plant-level specifications find more of a mixed bag with regard to the effect of local and non-local drought on different technologies, in part because of the equilibrium aspects of drought induced reductions in hydroelectric generation (Eyer and Wichman, 2018;

Qiu et al., 2023).

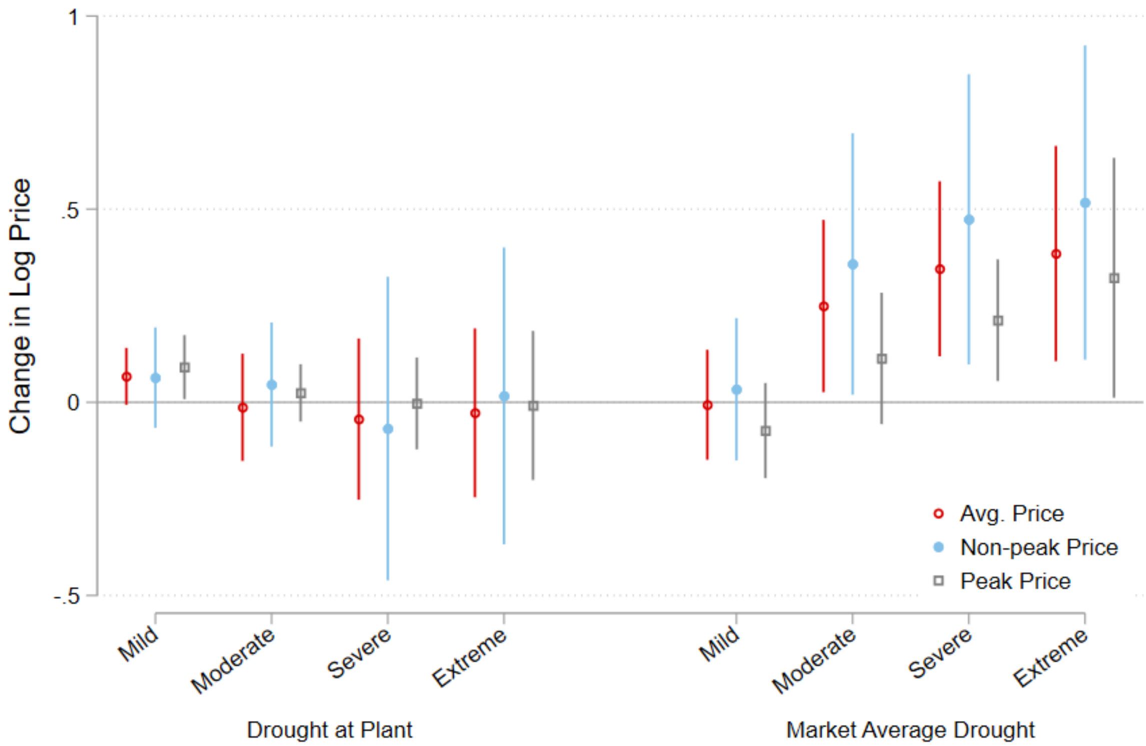
Overall the results from these analyses underscore the importance of accounting for market dynamics and are informative for beginning to consider subsequent price effects. First, the results showed that local drought conditions reduce generation from high water use plants, but otherwise have limited impact. Given that generation must equate to load, it is expected that generation somewhere in the market must be increasing. However, given that local drought likely only affects a small part of the market it is entirely possible that other plants are marginally increasing production, but the change is too small to be measured. In contrast, the results showed that for worse average drought everywhere else in the market there is significant growth in generation from dry plants. This aligns with the logic of the previous scenario in that the more high water use plants that are exposed to drought (via worse drought everywhere) the more substitute generation is necessary, and so the larger increase in generation from unaffected, dry cooled plants. As outlined in Section 2 though, dry cooled plants are generally operated last since they are more expensive than high water use plants. With these dry cooled plants coming online, it is reasonable to expect that average costs would increase as well as the wholesale energy prices, since the marginal plant is now more likely to be a relatively high cost dry cooled plant. The potential change in average efficiency of generating plants due to drought may be concerning for both maintaining affordable energy prices and the efficient use of inputs.

4.4 Prices

There is a limited relationship between local drought conditions and wholesale energy prices. In general, the left of Figure 5 shows that across all price measures the marginal effect estimates are not significantly different from zero. This aligns closely with the isolated impact of local drought on generation: conditional on drought elsewhere in the market, the localized change in output from a few plants is not likely to have a large enough impact on the market to result in significant price changes.

In contrast, there are economically and statistically significant increases in all three wholesale price measures as average drought elsewhere in the market worsens. For instance, the right hand side of Figure 5 shows a 35% increase in average wholesale prices received

Figure 5: Drought Effect on Wholesale Prices



Note Figure plots effect estimates for the impact of drough on the natural log of wholesale energy prices. Drought is defined as both drought at the plant's location (left panel) and the average drought everywhere else in the market (right panel). Non-drought conditions are the omitted category. Standard errors are clustered at the plant and month-of-sample levels. 95% confidence intervals are denoted by the vertical bars.

by plants in location l when average drought elsewhere in the market is severe, relative to non-drought conditions. In dollar terms, this equates to a \$8.28 increase relative to the mean price of \$23.66. As average drought elsewhere in the market worsens, more high water use plants are potentially being affected leading to a larger shock to aggregate generation. Since the dry cooled plants that come online to replace the lost generation are likely less efficient, the marginal plant filling demand is likely more expensive, pushing prices higher as more substitute production is needed.

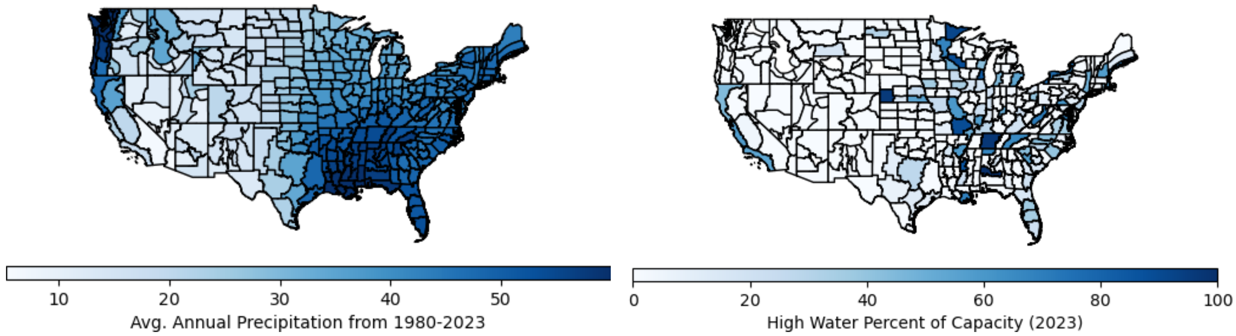
Non-peak prices consistently respond to drought more than peak prices, providing evidence that the price effect is driven by the difference in costs of the substitute price-setting plant relative to the original price-setting plant. To explore this dynamic, first consider non-peak hours when demand is low. Since lower marginal cost plants (non-thermals, high water use, low water use) should be operated first, in periods of low demand without drought the price setting plant is likely a low marginal cost plant. Under a drought shock though, by the previous analyses, generation by dry cooled plants increases so that the new price setting plant is likely a high cost dry cooled plant. Next consider peak hours when demand is high. To meet demand in absence of drought, the price setting firm is likely a dry cooled plant. With a drought shock, the price setting plant is still likely a dry cooled plant. Under the assumption that the difference in marginal costs between two dry cooled plants is less than the difference in marginal costs between a dry cooled and a not dry cooled plant, we would expect to see a relatively smaller increase in prices during peak hours. This is exactly what Figure 5 shows, highlighting the idea that the price effect magnitude is largely determined by the available substitute plants relative to the original price setting plant.

The general relationship between prices and drought highlighted here is similar to that documented in McDermott and Nilsen (2014). Since they use stream flow levels as their measure of water availability, direct comparison of the coefficient magnitudes is difficult. However the dose response follows a similar pattern as my analysis, with worse drought conditions increasing prices more.

4.5 Additional Analyses

I addition to the above analyses, I also examine several alternative specifications to look at the impact of drought on generation and prices, the results of which are summarized here and presented in more detail in Appendix Section C. I first test several alternative ways to measure variations in water supplies: precipitation, drought duration, and number of climate divisions in drought. The results suggest that prices are primarily influenced by the share of the market that is exposed to drought, more so than the severity of drought in any one location. I also examine the robustness of my results to alternative sample selection approaches. I find changing the sample selection process appears to have a limited impact on the main takeaways of the analysis.

Figure 6: Maps of Water Availability and Generation Mix



(a) *Note* Figure maps average annual precipitation from 1980 to 2023 for each climate division.

(b) *Note* Figure maps share of generation capacity that is high water use for each climate division as of 2023.

5 Empirical Evidence on Investment Decisions

Using average annual precipitation as a proxy for water availability, the eastern half of the US is both generally wetter than the western half (6a) and has a larger share of capacity that is high water use (6b) (Averyt et al., 2011). This correlation could reflect plants endogenously responding to drought conditions when making investment decisions. However, this simple cross-sectional correlation could also be capturing many other confounding factors, such as the eastern half of the US being more densely populated or being less productive for renewable technologies.

I explore the spatial correlation more carefully by using plant level analyses to compare investment decisions across plants within a climate division, exploiting temporal variation in the average local drought conditions before the investment decision. I focus on three steps of the investment process to define the outcome variables of interest: the probability that a constructed plant is technology type j, the probability an operating plant of type j is mothballed (shut down for an extended period[21]) and the retirement hazard of a type j plant. I find that worse drought shifts new capacity investments away from high water use plants and towards dry cooled. Once built, I find statistically insignificant increases in the retirement hazard of high water use plants after periods of worse drought. In total, the evidence is suggestive that plant investment is responsive to changes in drought conditions.

[21] In the data I classify observations with zero generation and that have had zero generation for at least 12 consecutive periods prior as being mothballed.

5.1 Methodology

I regress three measures of investment on average drought conditions in plant's location l over the τ periods leading up to the decision in period t, $\overline{\text{Drought}_{l,t-\tau}}$. For the sample of plants in the US[22], I estimate the following specification for plant i in location l in period t:

$$y_{i,t} = g(\beta\overline{\text{Drought}_{l,t-\tau}} + \Gamma X_{i,t} + \phi_l + \varepsilon_{i,t}) \tag{2}$$

For the outcome variable of technology choice at investment, $y_{i,t}$ is one of four binary variables the measures whether plant i built in period t uses technology type j, where j is high water use, low water use, dry or non-thermal. Since these outcomes are binary, the function $g(\cdot)$ is a probit transformation. With this specification, I measure drought over the ten years before period t, and the covariates $X_{i,t}$ consist of a categorical variable for decade of construction. For the binary outcome mothballing, I measure average drought over the year before period t while controlling for the average drought over the nine years prior to τ, a linear year trend, and a categorical variable for calendar month. I again use a probit specification. Lastly for retirement I use a Cox proportional hazards model, where I again define τ to be ten years and control for the year the plant was first operational. For all outcome variables I include a climate division fixed effect, ϕ_l and cluster standard errors at the climate division level. Additionally, to account for the large differences in capacity levels across technology types, I weight each plant by its capacity so that results can be interpreted with respect to a MW of generating capacity.[23]

5.2 Identification

Identification for these analyses comes from exploiting temporal variation in drought conditions within a constant climate division by linking drought to plants based on the timing of the decision of interest. By using variation of drought within a climate division, I can include climate division fixed effects to control for unobserved, time invariant environmental characteristics that could make a location more or less suitable to different technology types,

[22] Expanding from ERCOT to the US provides a larger sample of plant investment.
[23] I winsorize plant capacity at the 90th percentile of the technology specific distribution.

irrespective of drought. However, the analyses are conditional on a plant being planned/built in the first place, ignoring that this sample selection is potentially endogenous to drought conditions (e.g. worse drought increases electricity demand, increasing total investment in a location). Appendix Table A9 shows that there is not strong evidence that this is the case, with worse previous drought conditions in a location having no statistically significant relationship with total or new investment.

The goal of these exercises is to try and understand if firms change investment as a function of changes in future drought conditions. To do this I rely on the assumption that firms are informed by realizations of past drought shocks, so that the average drought conditions preceding decisions fully capture firms' expectations over future drought conditions. As a robustness to test the validity of this assumption, I repeat the analysis for the outcome of technology choice at investment while including the 10 year average drought after the plant was built. The results, shown in Appendix Table A7, show a zero coefficient on future drought which suggests that conditional on the information contained in past drought, future drought realizations are unrelated to investment. This supports the assumption that firms are basing their decisions on information available at period t, which is informed by past drought realizations.

5.3 Results

In total, the results from the analyses provide suggestive evidence that firms respond to drought conditions by investing in less water intensive technologies after worse drought. Panel A of Table 2 shows that a one standard deviation worse drought in the ten years before the plant is built is associated with a reduction in the probability that the plant uses high water use cooling of around 4.4 percentage points (14% over a base rate of 30 percentage points). Alternatively, worse drought increases the probability new plants are low water or dry cooled, with a relatively larger increase for dry cooled plants of 15%. With respect to mothballing in Panel B, there is limited statistically significant evidence of a relationship with either long run average drought or the drought in the previous year (separated into a categorical variable). It is notable though that for high water use plants the marginal effect point estimates are increasing with the previous year's drought severity, suggesting a higher

Table 2: Drought Correlation with Investment Decisions

	High Water Use	Low Water Use	Dry	Non-Thermal
Panel A: Probability plant uses technology				
$\overline{\text{PHDI}}$ 10 years before construction	-0.044*	0.026	0.021*	-0.001
	(0.026)	(0.028)	(0.013)	(0.007)
Mean Outcome	0.303	0.534	0.142	0.022
Observations	1,667	3,419	4,415	3,773
Panel B: Probability plant mothballed				
$\overline{\text{PHDI}}$ 10-1 years before	0.018	0.017*	-0.004	-0.001
	(0.014)	(0.009)	(0.004)	(0.002)
Mild PHDI last year	0.000	-0.010**	-0.001	-0.002
	(0.006)	(0.005)	(0.002)	(0.002)
Moderate PHDI last year	0.012	-0.008	-0.003	-0.002
	(0.012)	(0.005)	(0.003)	(0.004)
Severe PHDI last year	0.014	-0.005	-0.005	-0.001
	(0.018)	(0.006)	(0.004)	(0.002)
Extreme PHDI last year	0.045	-0.005	-0.006	0.000
	(0.037)	(0.007)	(0.006)	(0.002)
Mean Outcome	0.081	0.035	0.052	0.032
Observations	36,390	49,602	518,470	464,823
Panel C: Probability plant retired				
$\overline{\text{PHDI}}$ 10 years before	0.647	-0.626	-0.092	-0.615*
	(3.989)	(0.703)	(0.233)	(0.373)
Observations	196,286	206,907	913,717	610,775

Note Table presents correlations between historic standardized average drought and different decisions in the investment process. In Panel A the outcome variable is a indicator for whether a plant at time of construction uses the technology denoted in the column title, and drought is measured as the plant's location average PHDI value over the ten years before construction. In Panel B the outcome variable is an indicator for if a plant of the type shown in the column heading is mothballed in a period, and drought is measured as the plant's location average PHDI over the last year, categorized by severity, and the average over the nine years preceding the last year. In Panel C the outcome variable is an indicator for if a plant of the type shown in the column heading is retired in a period, and drought is measured as the the plant's location average PHDI value over the ten years before the period. Plants are weighted by capacity. Standard errors are clustered at the climate division level and shown in parentheses.

mothball hazard, while the point estimates are stable around zero for the other technologies. Lastly, turning to retirement, Panel C shows a statistically insignificant increase in the retirement hazard for high water use plants with a one standard deviation worse previous drought. Additionally, non-thermals have a statistically significant reduction in retirement hazard with worse drought over the decade before.

The results for changes in investment align well with the previous results on changes in production as a function of drought. The latter showed that experiencing a drought shock is costly for high water use plants, but increases production from dry cooled plants. Under this lens then, worse drought in the future would be expected to lower future returns to high water use investment and increase returns for dry cooled plants. These changes in return should translate into changes in investment, which follow identical patterns as to what the results in Table 2 show. These results therefore provide suggestive evidence that there is endogenous investment with respect to drought in electricity markets.

5.4 Additional Analyses

I addition to the above analyses, I also examine alternative measures of drought and investment with additional analyses, the results of which are summarized here and detailed in Appendix Section D. I first quantify the relationship shown in Figure 6 and find that conditional on key environmental variables, a one standard deviation increase in precipitation increases the share of capacity that is high water use in a climate division by 7 percentage points. With respect to alternative investment measures, I first use supplemental data on planned power plants to provide suggestive evidence that drought has similar impacts on investment before plants are constructed. Lastly, as an alternative to plant level analyses, I construct a climate division by decade panel. With this data set I find drought does not seem to be related to total investment but there is suggestive evidence that the plant level results hold with respect to technology specific investment.

6 Model Framework

This section presents a model of investment in capacity and electricity generation in ERCOT. The previous analyses showed that drought shocks shift production away from high water use plants and increase wholesale prices. Additionally, the previous results showed that over the long run worse drought is associated with shifts in investment away from high water use plants. Based only on these results, it is unclear what the full impact of drought due to climate change will be, since the effect depends on 1) the amount of high water use generation under the adapted generation mix and 2) the set of substitute plants available during times of drought. The model bridges this gap by incorporating drought as a determinant of production costs in the spot market, combining the direct impact of drought on production with the indirect changes working through the generation mix. The remainder of this section presents the model primitives, then works backwards through the market structure, starting with the spot market and ending with investment.

6.1 Model Primitives

The model is populated with heterogeneous firms, defined as a unique plant, categorized by two key characteristics. First, each plant is assigned one of four mutually exclusive technology types j: non-thermal, high water use, low water use, and dry. The technology type determines a plant's investment and production costs as well as its water needs - and therefore exposure to drought shock costs. Second, each plant is allowed to build in one of several locations $l \in L$, which determines the environmental shocks that the plant is exposed to.

The decision process of each plant in the model is outlined by the following structure. First, in an initial investment period (t=0) plants make a one time decision about how much generating capacity to build, given their type and expectations over future states and prices. Then in every subsequent period (month) of the finite lifetime of the plant, they compete in a repeated static spot market taking price as given and choosing how much electricity to generate. Plants are constrained by their initial capacity choice, so that they cannot produce more than their available capacity. The resulting market equilibrium is the set of capacity choices that maximize expected discounted profit flows and the market prices which ensure the spot markets clear.

The state variables, $\eta_{i,t}$, include price inelastic total load, D_t, and location specific environmental variables of temperature $tmp_{l,t}$, productivity of non-thermal generators $\omega_{l,t}$, and drought $z_{l,t}$. Drought is subject to both local and aggregate shocks, driving variation in market wide drought conditions. $\eta_{i,t}$ also includes production cost shocks, consisting of a persistent productivity factor ϕ_i and an idiosyncratic cost shock $\varepsilon_{i,t}$ drawn from a technology specific distribution.

Since the main focus of the model is the role of drought, I abstract from two prominent model features that are common in the energy markets literature. First, I treat both the investment and generation decisions as static problems instead of dynamic. For the investment decision, this modeling choice means that I am unable to look at the evolution of the generation mix in response to changing environmental conditions, but I am still able to capture changes in the stationary equilibrium mix. For the generation decision, this modeling choice ignores start-up and ramping costs, though since the model is at a monthly level these costs are likely less relevant. Second, I define all firms in the model as competitive, single plants instead of strategic or multi-plant firms. This modeling assumption is problematic if firms owning multiple plants respond to drought by strategically redistributing generation across plants in a way that differs from plant level profit maximizing behavior. While this type of behavior would likely drive my results to be attenuated toward a null impact, it seems unlikely that it is occurring.

6.2 Spot Market Generation

6.2.1 Non-thermal generation

The model assumes production by non-thermal plants is determined by exogenous environmental conditions in the plant's location and reduces the relationship into a simplified productivity measure, $\omega_{l,t} \in [0,1]$, that scales capacity. The amount of electricity produced by a non-thermal plant ($j = NT$) in a given period is

$$q_{i,t}^{NT}(\eta_t, K_i) = \begin{cases} 0 & \text{if } \omega_{l,t} + \phi_i + \varepsilon_{i,t} < 0 \\ (\omega_{l,t} + \phi_i + \varepsilon_{i,t})K_{i,t} & \text{if } \omega_{l,t} + \phi_i + \varepsilon_{i,t} \in [0,1] \\ K_{i,t} & \text{if } \omega_{l,t} + \phi_i + \varepsilon_{i,t} > 1 \end{cases} \tag{3}$$

The $\omega_{l,t}$, as reflected in Equation 12, captures aggregate and seasonal changes in productivity (eg. wind turbines produce less in summer). Persistent plant specific productivity differences (eg. a wind farm being in a windier location) are represented by ϕ_i, while $\varepsilon_{i,t}$ captures highly localized, time varying shocks. Plants are constrained by their capacity, so they cannot produce more than K_i or less than zero.

The per period profit received by non-thermal plants is simply

$$\pi^{NT}(\eta_t, P_t, K_i) = P_t q_{i,t}^{NT}(\eta_t, K_i) \tag{4}$$

Conditional on building capacity, subsequent generation is assumed to be costless for non-thermal plants. Therefore, each period non-thermal plants receive the wholesale price multiplied by their total output.

6.2.2 Thermal generation

Thermal plants takes prices as given and generate the quantity that maximizes current period profits which, under the assumption of a competitive market, is where the plant's marginal cost equates the market price. I parameterize the spot market production cost functions for each technology type using the following specification,

$$c^j(q^j_{i,t}) = \lambda^j_1 q^j_{i,t} + \lambda^j_2 \frac{q^2_{i,t}}{2K_{i,t}} + q^j_{i,t}(\rho^j z_{l,t} + \gamma^j X_{i,t} + \phi_i + \varepsilon_{i,t}) \tag{5}$$

This specification of production costs is microfounded in the regression analyses for the effect of drought on production and prices from Equation 1, and is similar to others in the literature (Butters, Dorsey, and Gowrisankaran, 2021; Reguant, 2014). Costs are non-linear in $q^j_{i,t}$, and in particular dependent on the level of production relative to capacity. I include a set of cost determinants, $X_{i,t}$, similar to those used in Equation 1, consisting of local temperature and its square, a linear year trend and month binaries. I also include permanent productivity differences, ϕ_i, and cost shocks $\varepsilon_{i,t}$. For this specification to accurately reflect plant production costs, I rely on the assumption that the observed market and environmental conditions are sufficient to capture changes in input costs, as well as the assumption that the non-linearities captured by λ^j_1 and λ^j_2 accurately reflect any non-linearities in production costs.

The parameter ρ^j is unique to my model, and captures the impact of drought on generation as a shift in production costs. This decision is based on anecdotal evidence that in response to water scarcity plants may bring in water from alternative surface water sources or pump groundwater to maintain production (Averyt et al., 2011). For notational simplicity, I denote the local drought conditions as $z_{l,t}$, but in practice I alow for non-linearities in the relationship by defining local drought conditions as falling into one of three categories: No drought, moderate to severe, or extreme. Additionally, all parameters are technology specific to capture the heterogeneous impact of drought shown in Section 4.

Under the cost function in Equation 5, profit maximization leads to the following optimal generation choice for thermal plants,

$$q^j_{i,t}(\eta_t, K_i) = \begin{cases} 0 & \text{if } P_t < \Lambda_{i,t} \\ \frac{P_t - \Lambda_{i,t}}{\lambda^j_2} K_i & \text{if } \Lambda_{i,t} < P_t < \Lambda_{i,t} + \lambda^j_2 \\ K_i & \text{if } P_t > \Lambda_{i,t} + \lambda^j_2 \end{cases} \tag{6}$$

$$\text{where } \Lambda_{i,t} = \lambda^j_1 + \rho^j z_{l,t} + \gamma^j X_{i,t} + \phi_i + \varepsilon_{i,t}$$

Plants cannot produce negative amounts of electricity[24], so for sufficiently low prices, $P_t < \Lambda_{i,t}$, plants do not generate anything. For prices above this "turn on" point, plants generate as a linear function of both price and capacity up until they reach their capacity constraint K_i. The capacity constraint physically limits output so that for $P_t > \Lambda_{i,t} + \lambda^j_2$ generation is perfectly inelastic at K_i.

The piece-wise linear optimal generation function gives rise to a piece-wise profit function for thermal plants that is linear in K_i for positive production.

$$\pi^j(\eta_t, K_i) = \begin{cases} 0 & \text{if } P_t \leq \Lambda_{i,t} \\ K_i \frac{(P_t - \Lambda_{i,t})^2}{2\lambda^j_2} & \text{if } \Lambda_{i,t} < P_t < \Lambda_{i,t} + \lambda^j_2 \\ K_i (P_t - \Lambda_{i,t} - \frac{\lambda^j_2}{2}) & \text{if } P_t > \Lambda_{i,t} + \lambda^j_2 \end{cases} \tag{7}$$

6.2.3 Wholesale Prices

The equilibrium spot market price is determined by the intersection of the aggregated thermal supply curve and the residual demand faced by thermal plants, defined as the total demand less the total amount of generation from non-thermal plants.

$$\tilde{D}_t = D_t - Q^N_t - \sum_{i \in NT} q^{NT}_{i,t}(\eta_t, K_i) \tag{8}$$

[24]Empirically, this is not true. Idling plants may consume low levels of electricity while waiting to begin generating, so that plants that are idle for long periods (like peaker plants) may consume more electricity than they generate (EIA, n.d.).

Given the capacity choices of the non-thermal plants, $\tilde{D}_t$ is stochastically determined. Aggregating the individual supply curves results in an aggregate thermal supply curve $Q^T(P_t; \eta_t, K_i)$ that is a linear piece-wise function over P_t, shaped by the state variables and capacity choices. Inverting the aggregate supply curve at $\tilde{D}_t$ returns the market clearing price $P_t^* = Q^{T^{-1}}(\tilde{D}_t; \eta_t, K_i)$.

The market clearing price is undefined if there is insufficient capacity to meet demand. In these situations, the generators physically cannot supply enough electricity, resulting in blackouts. Alternatively, there is not a unique price if non-thermal generation is sufficient to entirely fill demand.

6.3 Investment in Capacity

6.3.1 Investment value function

In the initial investment period $t = 0$, each plant chooses how much generating capacity to build to maximize the stream of discounted expected future profits, less investment costs. The value a plant receives from building capacity amount K_i is

$$V(K_i) = \mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi^j(\eta_t, K_i)] - \delta_1^{j,l} K_i - \delta_2^j K_i^2 - \nu_i K_i \tag{9}$$

In period $t = 0$, the plant must pay the investment costs of building capacity, which are assumed to equal a quadratic in capacity plus an idiosyncratic cost shock $\nu_i K_i$, which is known to the plant at the time of investment. Once built, plants receive profits in each subsequent period from participation in the spot market. The profit each period depends on the capacity choice K_i and the realized state variables η_t. Plants produce over a finite horizon of T^j months, and discount future profits at a rate of β. Maximizing $V(K_i)$ with respect to capacity returns the optimal capacity choice as a function of marginal profits

$$K_i^* = \frac{\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, K_i^*)] - \delta_1^{j,l} - \nu_i}{2\delta_2^j} \tag{10}$$

The investment cost parameters, lifespan, and profit function are all technology type specific, as shown by the superscript j. In particular, investment costs are technology specific to account for different infrastructure needs, such as low water use plants requiring additional investment in cooling towers resulting in a cost which other plant types do not face. I additionally allow for spatial variation in the linear investment cost parameter, denoted by the superscript l, to capture spatial differences such as access to transmission infrastructure and land use. Additionally, since any fixed operating costs in the spot market are not separately identified from the linear investment costs, allowing spatial heterogeneity captures some variation in unobserved fixed operating costs.

6.3.2 State transitions

Uncertainty from a plant's perspective in $t = 0$ is over the realization of future state variables and the resultant market clearing wholesale prices. For future state variables, environmental variables and demand are allowed to be correlated, both across space and time, with their distributions known to the plants in period $t = 0$. The model formalizes these relationships through the following set of reduced form law of motion equations, where $f(\cdot)$ denotes a linear function.

$$tmp_{l,t} = f_{tmp,l}(year_t, month_t, v_t^{tmp}, u_{l,t}^{tmp,l}) \tag{11}$$

$$\omega_{l,t} = f_{\omega,l}(year_t, month_t, v_t^{\omega}, u_{l,t}^{\omega,l}) \tag{12}$$

$$z_{l,t} = f_{z,l}(z_{l,t-1}, tmp_{l,t}, v_t^{z}, u_{l,t}^{z,l}) \tag{13}$$

$$D_t = f_D(year_t, month_t, \overline{tmp_t}, \overline{tmp_t^2}, D_{t-1}, P_{t-1}, v_t^D) \tag{14}$$

The over line notation denotes the market average of the state variable. Notice the resulting distributions of the environmental state variables in Equations 11-13 are location specific, seasonal (except z), subject to an idiosyncratic shock $u_{l,t}$, and correlated across space through a common shock v_t. Drought is both auto-correlated and correlated with local temperature, reflective of the natural hydrologic processes leading to drought (Hoerling, 2018). Additionally, while load is correlated with lagged prices, it is perfectly inelastic with respect to current prices P_t. This assumption stems from the structure of electricity markets where contracting between load serving entities and energy producers results in lagged pass through of prices, so that the end price consumers pay, and respond to, is an average of previous prices, P_{t-1}, and not the current spot market price itself, P_t.

Forming expectations over future prices in period $t = 0$ is complicated by the fact that prices are an equilibrium object, determined in part by each plant's capacity decision. Given the static set up of the problem, plants are simultaneously choosing capacity with imperfect information over other plants' investment and eventual production costs. For tractability, I assume that plants abstract from the underlying game and instead approximate future prices $\hat{P}$ as the common knowledge function:

$$\hat{P}_t = f_{\hat{P}}(year_t, month_t, \overline{tmp_t}, \overline{tmp_t^2}, \overline{z_t}, \overline{z_t^2}, \overline{\omega_t}, D_t, \hat{P}_{t-1}, v_t^P) \tag{15}$$

This structure assumes first that realizations of key state variables are sufficient to represent the underlying spot market process, and second that plant investment does not impact future prices. Under these assumptions, and with the law of motions for state variables, plants can form expectations over future profit streams to solve for their optimal capacity investment with the modified version of Equation 10:

$$K_i^* = \frac{\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, K_i^*, \hat{P}_t)] - \delta_1^{j,l} - \nu_i}{2\delta_2^j} \tag{16}$$

7 Model Estimation

I estimate the model in two steps working backwards. I start by estimating the production cost parameters for the spot market and the state space transition parameters. I use these to construct the estimates of expected marginal profit flows used to estimate the investment cost parameters.

7.1 Spot Market Production Costs

I estimate the parameters governing the marginal cost functions from the firms' first order conditions. The firm first order condition returns ${q^*}_{i,t}^j$ as in Equation 6, which is replicated and slightly rearranged in Equation 17. This provides a structure to estimate the cost function parameters with regression analysis, given data on the plant level total amount generated $q^j_{i,t}$, capacity K_i, equilibrium market average wholesale price P_t, and environmental and market covariates.

$$\frac{q^{*j}_{i,t}}{K_i} = \begin{cases} 0 & \text{if } P_t < \Lambda_{i,t} \\ \frac{P_t - \Lambda_{i,t}}{\lambda^j_2} & \text{if } \Lambda_{i,t} < P_t < \Lambda_{i,t} + \lambda^j_2 \\ 1 & \text{if } P_t > \Lambda_{i,t} + \lambda^j_2 \end{cases} \tag{17}$$

$$\text{where } \Lambda_{i,t} = \lambda^j_1 + \rho^j z_{l,t} + \gamma^j X_{i,t} + \phi_i + \varepsilon_{i,t}$$

I estimate Equation 17 with a tobit regression model, estimated with maximum likelihood. In absence of the capacity constraints, the firm's optimal $\frac{q^{*j}_{i,t}}{K_i}$ would equal $\frac{P_t - \Lambda_{i,t}}{\lambda^j_2}$. However, because of the capacity constraints the generation amount observed in the data $\frac{q^j_{i,t}}{K_i}$ is a censored version of the optimal generation choice, leading to the Tobit specification. Note that this specification is essentially identical to that used in the analyses of generation based on Equation 1.[25]

Similar to the discussion in Section 4, the identification of most of the cost function parameters stems from temporal variation. In particular, the cost parameters on drought are identified from linking deviations from normal hydrologic conditions with changes in plant level production. Identification of λ^j_1 and λ^j_2 is more complicated, since P_t is an equilibrium object, and therefore a function of $\varepsilon_{i,t}$. With aggregate shocks causing cross-sectional correlation in $\varepsilon_{i,t}$, estimates for λ^j_1 and λ^j_2 will be biased.[26]

I therefore instrument for P_t with total load D_t, the market average drought $\overline{z_{l,t}}$, and total generation from non-thermals $\sum_{i \in NT} q^{NT}_{i,t}(\eta_t, K_i)$. The first stage parameters are estimated concurrently within the Tobit maximum likelihood estimation. Demand is both a relevant instrument for price, reflected by the high F-statistics shown in Table 3, and exogenous since demand is short-run price inelastic. A risk to demand being a valid instrument

[25]Two key differences between Equations 1 and 17 are that I define only two categories of drought and use the market average price instead of hub price to estimate Equation 17. I use the market average price to maintain consistency with the model set up, though the parameter estimates are robust to using hub prices.

[26]While I include a linear year trend and month fixed effects to control for cyclical aggregate shocks, there remains correlation from market wide, one-off shocks such as changes in fuel prices.

is if the aggregate shock part of $\varepsilon_{i,t}$ is autocorrelated. As shown in Equation 14, demand is long-run price elastic so that if the aggregate shock part of $\varepsilon_{i,t}$ is autocorrelated, the dependence of D_t on P_{t-1} results in correlation between D_t and $\varepsilon_{i,t}$. This channel of bias is likely quite weak though, since determination of demand is dominated by seasonality and temperature variation. Regressing D_t on a linear year trend and month fixed effects results in an R^2 value of 0.94 (Appendix Table A12), leaving relatively little room for robust correlation with the aggregate shock. I also include the instrument of market average drought to capture the indirect effect of drought through changes in the market equilibrium documented in Section 4. Lastly, I include the instrument of total generation from non-thermals since this has no direct impact on thermal plant generation except through changing the wholesale price.

The estimated cost parameters are presented in Table 3. The first row shows the estimates of the cost curve curvature (λ_2^j) with respect to generation. This parameter is lowest for dry cooled plants, suggesting they are relatively price elastic while low water use plants are the least elastic. Additionally, using the full set of cost parameters to trace out the marginal cost curves for each plant type shows that high water use and low water use plants are consistently cheaper than dry cooled plants (Appendix Figure A12). This implies high water and low water use plants come online first, while the more expensive dry cooled plants operate as peaker plants - in line with anecdotal descriptions of these technologies.

The key parameters of interest, ρ_1^j and ρ_2^j, show that drought significantly increases costs only for high water use plants. For high water use plants, moderate to severe drought increases marginal production costs by \$16.26/MWh while extreme drought increases costs by \$35.29/MWh. Compared to an average wholesale price of \$24/MWh, these estimates reflect substantial increases in operating costs.

7.2 State Transition Parameters

I estimate the parameters dictating the transition of state variables over time (Equations 11-14) offline using the available data for plants in ERCOT from 2000 through 2022.[27]

[27] Because of the relatively low penetration of non-thermals and rapid technological changes in efficiency in the beginning of the sample, I restrict the data to 2015-2022 for estimating the renewable capacity factor transition parameters.

Table 3: Cost Function Parameters

	High water use	Low water use	Dry
Capacity used: λ_2^j	577.9***	701.6***	448.6***
	(177.4)	(134.8)	(45.28)
Moderate-Severe: β_1^j	16.26***	0.147	-0.672
	(5.302)	(3.082)	(1.707)
Extreme: β_2^j	35.29***	1.573	-1.248
	(8.957)	(5.160)	(3.071)
F-stat	269	1745	2319
Observations	1,960	8,963	10,997

Note Table presents parameter estimates for thermal firm cost functions. Parameters are estimated separately for each technology type. The estimate marginal cost at the average level of generation and the first stage F-statistic are shown at bottom. Standard errors are shown in parentheses.

For temperature, drought, and renewable capacity factors, I estimate the parameters using ordinary least squares with a location level panel. For quantity demanded I use ordinary least squares with market level time-series data.

I ensure the transition parameters for predicted prices, $\hat{P}_t$, are internally consistent when constructing the estimate of $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$ used for estimating the investment cost parameters. Using the observed capacity in the data and the estimated state variable transition parameters, I simulate a series of state variable draws. Given the realized state variables, I solve for the equilibrium prices each period with the inverse aggregate supply curve. I then use these simulated equilibrium prices to estimate new transition parameters for $\hat{P}_t$. Because demand is dependent on lagged prices, the process must be repeated for parameter convergence.

I follow a similar routine to ensure the transition parameters for predicted prices used in the counterfactual scenarios are internally consistent. Because investment is allowed to change in the counterfactual analyses, the resulting equilibrium price process may also change. To accomodate this I follow the process presented by Lee and Wolpin (2006). First, I use the parameters estimated from the data to simulate the optimal investment in the market given the counterfactual state variables distributions. Second, given the simulated capacity, I simulate a series of state space draws and equilibrium prices to re-estimate the transition parameters for Equation 15 in the same way as previously described. Using the updated parameters, I resolve for optimal investment and repeat the whole process until convergence of the transition parameters for the price process. The resulting estimated transition parameters for the price process reflect the modeled plants having internally consistent beliefs over future prices given the changed environment.

7.3 Investment Costs

I use the plant first order condition from Equation 10 to estimate the investment cost parameters. Under Equation 10, the optimal level of new capacity investment is a linear function of expected future marginal profits, $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$, and an idiosyncratic investment cost shock, ν_i. I assume that

$$\nu_i \overset{\text{iid}}{\sim} N(0, \sigma_\eta^j) \tag{18}$$

and that it is uncorrelated with the production shocks ($\varepsilon_{i,t}$) faced by the firm. By Equation 7, profit each period is linear in K_i, so that in combination with independence of η_i and $\varepsilon_{i,t}$, $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$ is exogenous. I regress K_i on $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$ using technology specific subsets to capture heterogeneity in investment costs. Due to small samples, I combine high water and low water use plants, but include binary variables so that the linear term $\delta_1^{j,l}$ is type specific. Additionally, due to potentially thin samples within each climate division, I cluster divisions into three larger regions based on tercile of population density and estimate a unique linear investment cost for each larger region.

I first numerically solve for $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$ for each plant by simulating a series of state space and wholesale price draws following Equations 11-15. I detrend the state variables with respect to year to accommodate the one-time investment structure. I measure capacity investment in the data as the plant level total capacity as of December 2022.

Two challenges for estimation arise from the censoring of investment at zero. First, the capacity measured in the data reflects a censored version of the true optimal capacity from Equation 10 since observed investment must be non-negative. I account for this by using a Tobit regression with censoring at zero. Second, the data set only contains observations of plants that have ever existed in ERCOT since 2000, and necessarily excludes hypothetical plants that were never constructed. This sample selection could bias the estimated cost

Table 4: Investment Cost Parameters

	Non-thermals	High water use	Low water use	Dry
Linear cost: $\delta_1^j/1{,}000$				
Low Pop. Density	600.71***	1,983.43***	4,019.43***	1,790.27***
	(131.67)	(433.00)	(585.28)	(106.16)
Mid Pop. Density	960.65***	1,932.06***	3,915.33***	1,644.53***
	(73.73)	(362.78)	(448.26)	(82.33)
High Pop. Density	814.02***	1,792.11***	3,631.73***	1,514.72***
	(56.67)	(220.13)	(184.00)	(17.55)
Quadratic cost: $\delta_2^j/1{,}000$	1.75**	0.08	0.16	0.81**
	(0.73)	(0.09)	(0.17)	(0.33)
Cost shock standard deviation: $\sigma_\nu^j/1{,}000$	641.39	206.42	418.31	268.18
Estimated cost per MW (millions)	.9400000000000001	1.9	3.82	1.55
EIA cost per MW (millions)	1.4	1.1-2.7	1.1-2.7	0.5

Note Table presents parameter estimates for investment cost parameters. Parameters are estimated separately for each technology type (column). There are no high water use plants in the southern region of Texas, so the linear investment cost cannot be estimated. Total estimated investment costs at the median capacity investment observed in the data and reported (EIA) estimates of median construction costs are shown at bottom. Standard errors are shown in parentheses.

parameters by ignoring a relevant subsample of plants. To address this, I incorporate a set of "never-constructed" plants into the sample, each with zero capacity and an expected marginal profit constructed following the same process as for the real plants.

The estimated investment cost parameters are shown in Table 4. Across all technologies marginal costs are convex in capacity size, reflected in the positive values for δ_2^j. I find that investment costs are lowest for non-thermal plants, with 250 MW of capacity costing \$333 million. 250 MW of dry capacity in contrast costs \$2 billion, while comparably sized high water use and low water use thermals would cost \$1.5 and \$3.5 billion respectively. Additionally, using the location specific linear investment costs I find that building thermals plants is relatively cheaper in more population dense areas, while building non-thermals is relatively cheaper in less densely populated areas. This is reasonable given the land use requirements for the different technologies.

My total estimated plant costs for low water use thermals are similar to estimates from Gowrisankaran, Langer, and Reguant (2024), who find a 250 MW combined cycle natural gas (comparable to a high or low water use thermal) investment costs on average \$1.6 billion. However, the per MW investment cost of the median investment is generally substantially larger than construction cost estimates from the EIA for approximately comparable plants, as shown in the last two lines of the table.[28] It is reasonable that my estimated costs are larger though, since there are additional costs to plant construction beyond the physical construction costs such as siting permits or community negotiations.

7.4 Model Fit

I find that the modeled spot market process produces market outcomes that align closely with the data. I test the model fit of the spot market stage of the model, I simulate state space realizations and solve for the equilibrium price. The results of this exercise are shown in column 2 of Table 5. Panel A of the table shows that capacity investment compared to the data are mechanically identical. With respect to prices, Panel B shows that the spot market process is matching prices closely on average, though matching less well when looking at prices by non-drought and drought periods. Additionally, as shown in Panel C, modeled prices are more volatile than prices in the data.

Incorporating the investment decision into the model makes the model fit the data worse. As shown in the third column of Panel A, the model over predicts investment in non-thermals and dry cooled plants, and under predicts investment in high and low water use plants. These differences in investment result in the equilibrium prices being consistently higher and more variable than in the data.

8 Counterfactual Drought Scenarios

This section presents counterfactual analyses, simulating investment and production in ERCOT under alternative climate scenarios. The goal of this exercise is to understand 1) to what extent does the investment response mitigate the drought impact and 2) what does the full effect of climate-diven drought look like. To do this I compare the market equilibriums across two simulations, one with and one without endogenous investment.

[28]Note that engineering estimates generally focus on investment costs by prime mover and fuel type, not cooling system. To provide approximate comparisons, I compare high water use and low water use plants to investment costs for non-combustion natural gas plants.

Table 5: Model Fit

	Data	Data Capacity Simulated Market	Simulated Capacity Simulated Market
Panel A: Capacity Share			
Non-thermal	0.39	0.39	0.38
High Water	0.11	0.11	0.11
Low Water	0.37	0.37	0.35
Dry	0.13	0.13	0.15
Panel B: Average Price			
Average	23.82	23.23	24.83
Non-drought	20.59	18.89	20.70
Drought	30.28	34.51	36.14
Panel C: Price Standard Deviation			
Average	13.66	25.99	24.61
Non-drought	9.50	22.18	21.12
Drought	17.78	30.21	26.60

Note Table compares simulated market results relative to the data. Column 1 shows the data moments, column 2 shows the simulated price moments using capacity investment observed in the data, and column 3 shows the simulated investment and price moments, simulating both investment and the spot market.

I model future drought conditions using estimated drought index PDFs calculated by Zhao and Dai (2022) under two alternative climate possibilities.[29] The forecasted drought conditions come from simulations by 25 different climate models within the Coupled Model Intercomparison Project (CMIP6) using two alternative emissions scenarios: Low-to-Moderate and High emissions.[30] Using the PDFs from Zhao and Dai (2022) I transform each location specific PHDI distribution, shifting the mean and increasing the standard deviation. For the Low-to-Moderate emissions scenario, the mean PHDI is increased by one and the standard deviation increased by 0.3. For the High emissions scenario, the mean PHDI increases by 2 and the standard deviation increases by 0.5. Transforming the PHDI densities this way assumes that climate change will change drought conditions uniformly across Texas, but

[29] Zhao and Dai (2022) model the self-calibrated Palmer drought severity index with Penman–Monteith potential evapotranspiration (scPDSIpm) which measures drought on a shorter hydrologic timeline than the PHDI. Given the two indexes are similarly constructed from evapotranspiration, runoff, and precipitation, I assume that the PHDI would experience identical distributional changes as the scPDSIpm.

[30] The CMIP6 is a collection of alternative climate models from different climate research centers around the world. The goal of CMIP6 is to facilitate model comparison using standardized scenarios. These scenarios are called Shared Socio-economic Pathways (SSPs), and represent alternative climate futures based on societal changes such as population growth, urbanization, or land use changes (*CMIP6 and Shared Socio-economic Pathways overview* n.d.). The estimates of drought conditions from Zhao and Dai (2022) are available for SSP2-4.5 and SSP5-8.5.

Table 6: Simulated Total Investment (MW)

	Baseline	Low-to-Moderate	High
Non-thermal	67,054.58	67,080.88	67,107.82
High Water	6,778.17	6,073.51	5,397.31
Low Water	31,698.92	31,636.16	31,561.12
Dry	38,732.30	39,007.74	39,304.76

Table 7: *Note* Table presents simulated total capacity investment in MW by technology type. The first column denotes the simulation using the historic drought distribution while the second and third columns use the projected drought distributions under the Low-to-Moderate and High scenarios.

recognizes the initial heterogeneity in environmental conditions.[31]

I use the following process to solve for the counterfactual equilibrium market outcomes. For each plant in the sample, I first solve for $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$ as of December 2022. In simulations with endogenous investment, the $\hat{P}_t$ and η_t used to calculate $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$ depend on the counterfactual drought distribution. In simulations without endogenous investment, the $\hat{P}_t$ and η_t used to calculate $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$ depend on the original drought distribution from the data. I then simulate optimal capacity investment following Equation 10. Lastly, I repeatedly simulate the spot market process to solve for P_t as a function of the simulated capacities and state variables, based on the counterfactual drought distributions.

I first consider the change in investment across the alternative scenarios, shown in Table 7. I find that investment in high water use technologies declines by 705 MW relative to the Baseline simulations under the Low-to-Moderate scenario and 1,381 MW under the High scenario. From the initial investment level, the reduction in investment under the High scenario is equivalent to about 20%. In contrast, investment in dry cooled plants increases by 572 MW between the Baseline and High scenarios, while investment in the other technologies is only negligibly changed. Across the scenarios, the level change in capacity suggests that the impact of future drought on investment is roughly linear in the average drought increase.

I next examine the resulting equilibrium prices, comparing outcomes across the al-

[31] I keep the transition parameters for drought and the other non-price state variables the same as estimated in the data, since without further data or assumptions I cannot reliably estimate them under alternative conditions. The consequences of this modeling limitation are unclear, as worse future drought will likely increase temperatures and subsequent demand, while technological innovation may reduce total electricity demand.

Table 8: Simulated Equilibrium Prices

	Baseline		Low-to-Moderate		High	
	Exog	Endog	Exog	Endog	Exog	Endog
Average	32.53	32.53	32.84	35.00	33.16	35.03
Non-drought	27.02	27.02	25.58	27.68	24.46	26.22
Drought	47.61	47.61	43.35	45.57	40.62	42.61

Table 9: *Note* Table presents simulated equilibrium prices on average, during non-drought periods, and during drought periods. The first set of columns denotes the simulation using the historic drought distribution while the second and third columns use the projected drought distributions under the Low-to-Moderate and High scenarios. Columns denoted Exog are estimated using the simulated technology mix under Baseline conditions (Column 1 of Table 7). Columns denoted Endog are estimated using the simulated technology mix under the respective climate scenario.

ternative climate scenarios both with and without adaptation of the technology mix. The results under the exogenous technology mix can be interpreted as similar to existing work by extrapolating from historic effect estimates, while the model framework incorporates market dynamics in a more rigorous way. I find that when ignoring adaptation but capturing market dynamics, worse future drought results in a limited change in the average energy price (Columns 1, 3, and 5 of Table 9). This is a result of more frequent drought mechanically resulting in more drought periods (increasing the average price) but less demand due to the higher prices (decreasing the average price). This finding shows that simply extrapolating from historic drought shocks is potentially missing key market dynamics.

Next, considering the role of endogenous investment, I find that the drought driven shift in the generation mix does not decrease drought-period electricity prices relative to the scenarios without adaptation. In contrast, under the adapted generation mix prices are consistently higher. This surprising result is likely coming from the growth of dry cooled plants which are relatively very costly to operate.

9 Conclusion

Climate change is exacerbating drought conditions around the world. Given the key role of electric grids in society, it is important to understand how a changing hydrologic landscape may affect this water intensive sector. This means understanding both the response in the spot market to a drought shock and accounting for potential adaptation of the grid through changes in investment.

This paper examines the potential impact climate change-driven drought may have on electricity markets. I first look at how drought shocks have previously impacted equilibrium generation and prices, and find that local drought shifts generation away from high water use plants towards dry cooled plants and leads to significant price increases. I then look at if firms responded to perceived changes in drought risk when investing in existing power plants. I find that firms do appear to respond to drought when investing in new capacity by shifting towards less water intensive technologies. I then forecast what the equilibrium mix of generating technologies would look like under alternative climate futures, and explore how equilibrium generation and prices subsequently change. I find that in line with the reduced form analyses, investment shifts away from high water use plants and towards dry cooled. Additionally, I find that the subsequent electricity prices are higher under the alternative technology mixtures. Extrapolating from existing literature would suggest that the increases in electricity prices would lead to regressive reductions in welfare, through reduced purchasing power and increases in temperature-related mortality (Pashardes, Pashourtidou, and Zachariadis, 2014; Chirakijja, Jayachandran, and Ong, 2024).

Additionally, the growth of relatively inefficient dry cooled plants raises concerns with respect to exposure to pollution from plants. To begin exploring this dynamic, I link my sample of ERCOT plants to emissions data from the EPA's Clean Air Markets Program Data. This data shows that dry cooled power plants in my sample produce on average 9% more short tons of CO_2 per MWh of electricity generated than high water use plants. Using this statistic, a simple back of the envelope calculation shows that the change in investment under the High simulation would result in an increase in CO_2 emissions of 9,405 short tons. This equates to about a 7% increase in overall CO_2 emissions from electricity generation in ERCOT.

While the analyses generally focus specifically on Texas, it seems reasonable that results from this analysis would extend to the rest of the US. Additionally, because high water use technologies make up a significantly larger share of generation for the US as a whole than in Texas, as shown in Table 1, the results from this analysis may be a lower bound for the US wide effect of climate change induced drought. The Texas only analysis shows that drought adversely impacts markets through high water use generators, with a larger impact as a function of the extent the market is exposed to drought. Having high water use generators be a larger player for the US market could increase the share of the market suseptible to drought, leading potentially to larger impacts. However, since the US as a whole is physically larger, larger spatial variation in drought conditions would likely help mitigate some of the risk. While the structural model used in this paper is readily extendable to the US at large, more data would be needed to account for spatial heterogeneity in prices, costs, and transmission losses.

In addition to extending the scale of the analyses, there are several other avenues for further progress in this line of research. First, I generally abstract from the role of natural gas prices in determining investment and production. This is likely ignoring an important channel through which climate change will further impact electricity markets. Since hydraulic fracturing is also an extremely water reliant industry, worsening drought may further impact markets through increasing natural gas prices. Second, I employ a static decision model instead of a dynamic framework which prevents me from studying the timing of investment shifts with respect to drought shocks. This is an interesting area for policy, since is is ex ante unclear how precise firms beliefs are over future environmental conditions, and providing information could be a cheap and effective solution to facilitate adaptation. Lastly, the world of electricity generation is rapidly changing with new technologies and a proliferation of energy storage. While increased storage will likely help mitigate risk from climate change, an important caveat to note is that currently 96% of energy storage capacity is through pumped-storage power plants which are entirely powered by water. The effect on markets from climate change through these storage sources is another area in need of further research.

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Appendices

A Background Supplement

A.1 Details on ERCOT Market

The market in ERCOT is an aggregation of three separate, sequential markets. In the first market, the bilateral forward market, generating firms sell electricity directly to utilities under forward contracts, well in advance of the realized load. The majority of transactions in the whole sale market occur in the forward market. Generating firms then sell electricity to ERCOT through a bidding process in the day ahead market, which occurs one day before load is realized at 15 minute intervals. ERCOT purchases electricity so that the sum of generation in the day ahead market and the bilateral forward market equals the expected load at lowest cost. Lastly, firms again sell to ERCOT through a bidding process in the real-time market, which occurs every five minutes. ERCOT purchases electricity so that the sum of generation in the real-time market, the day ahead market, and the bilateral forward market equals the realized load at lowest cost. Because firms have the opportunity to operate in all three markets, prices across the three markets are highly correlated (ERCOT IMM, 2023).

Within the day ahead and real time markets there are also smaller "markets" which occur as a result of physical transmission constraints (congestion) during periods of high demand. Because of this submarket dynamic, ERCOT allows wholesale energy prices to be location specific. The location specific prices are averaged up to a regional level "hub price" for five different hubs covering the ERCOT service area. During uncongested periods when electricity can flow freely across space the hub price equals the market average price. However, during congested periods the hub price may differ from the market average price leading to cross-sectional variation in the price generating firms receive.

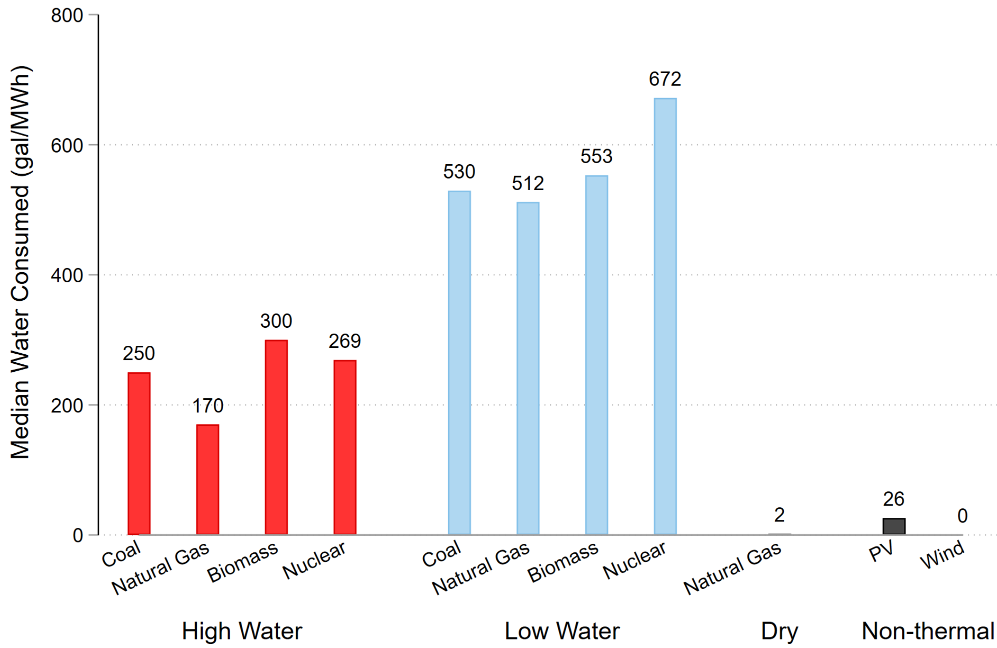
A.2 Details on Electricity Generation and Cooling

Almost all generating technologies produce electricity by spinning a turbine. Non-thermal plants, like wind and hydroelectric, spin turbines using non-heat energy sources, namely wind and water. Thermal generators, on the other hand, combust fuel to heat pressurized steam and/or gas (called the *prime mover*), which are in turn used to spin a turbine. Due to differences in the process of heating steam versus gas, the prime mover determines the speed at which a generator can change production. Additionally, the prime mover impacts how much heat energy is needed to produce 1 MWh of electricity, which translates into the generator's thermal efficiency. Generally, generators with higher thermal efficiency (i.e. combined steam and gas and to a lesser extent steam only) are slower to change production than less efficient generators (i.e. internal combustion and gas turbines) (EIA, 2023; Joshi et al., 2020).

While many generators use steam as the prime mover, the system used to cool the prime mover after generation is actually the thirstiest part of the process. Cooling systems can be categorized into three general groups: once-through, recirculating, and dry. Once-through cooling systems (in this paper called high water use) pull water from a nearby source, cool the prime mover through conduction, and then return the now heated water back to the original source. Recirculating (low water use) pull water from a nearby source, cool the prime mover through conduction, and then cool and re-use the water until it is fully evaporated away. Dry systems use air instead of water to cool the prime mover through convection.

Besides determining the water needs of the generation process, the cooling system is important since it can impact overall thermal efficiency. From the Rankin cycle, having a larger change in temperature of the prime mover over the generation process leads to higher thermal efficiency. Because once-through systems are continually using new water they are better able to cool the prime mover back to lower temperatures after generation, resulting in a larger change in temperature over the generation process. In contrast, recirculating systems re-use water so that as it heats up it is more difficult to cool the prime mover to lower temperatures, resulting in a smaller change in temperature over the generation process.

Figure A1: Water Consumption by Technology



Note Figure plots the median volume of water consumed per MWh of electricity produced. Technologies are disaggregated along the x-axis, first by cooling and then by fuel type. Values are collected from Macknick et al. (2011).

Similarly, dry cooled systems are less efficient at reducing the temperature of the prime mover. These differences in cooling result in meaningful differences in thermal efficiency of plants (World Nuclear Association, 2020; EPRI and Commission, 2002).

It is relevant to note that water withdrawn does not equate to water consumed. Once-through cooled systems withdraw large volumes of water but return the majority of that water to the source. In contrast recirculating systems end up consuming almost all of the water withdrawn (see Figure A1). While consideration of consumption is important for water management and downstream users, it is beyond the scope of this paper.

B Data Supplement

As discussed in the main body of the paper, I construct the panel used in this paper by combining data from several sources. I detail the construction process below.

B.1 Plant Characteristics

Capacity, dates, and location I start with data from the US Energy Information Administration (EIA) to identify power plants in the US. Using the EIA-860 forms which collect generator-level data for plants with at least 1MW of capacity, I compile a roster of all operating and retired generators in the US since 2001. I consider only power plants in the contiguous US. Each generator observation contains information on the generator's location, capacity, year and month of first operation and retirement, and a unique id for the power plant where the generator is located. I expand this roster into a monthly panel of generators. This is then aggregated into a panel of power plants containing information on plant operating/retirement dates and capacity. I define the date the plant is first operating as the earliest observed operating time of a generator at the plant. I define plant retirement similarly as the latest retirement of a generator, if all generators are retired. I then define plant level capacity each month as the sum of capacities of generators that are operating during that month.[32]

Fuel and prime mover Assigning plant level fuel type (coal, hydroelectric, natural gas, nuclear, etc) and prime mover (combustion, steam, or combined) is difficult since each plant can house multiple types of generators. To find the primary fuel and prime mover used for each plant, I use the capacity weighted modal technologies. Specifically, I identify the type of fuel and prime mover that have the largest share of operating capacity each year for each plant. I then define the primary fuel and prime mover as the technologies that most often have the largest capacity share at the plant over the sample period.

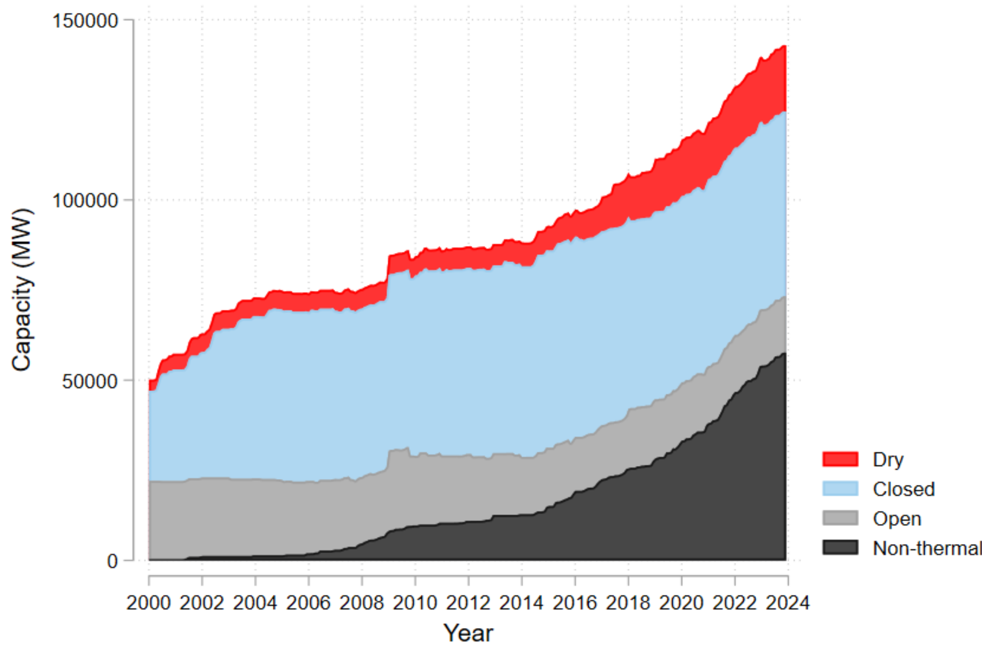
I define thermal plants as those that primarily use coal, natural gas, or petroleum for fuel. I omit nuclear and solar thermal generators from the thermal category, even though

[32] A plant is operating if it is after the date of first operation but before the retirement date.

they are technically thermal generators and nuclear generators are extremely water intensive. Nuclear plants have unique operating requirements, making them operate as "must-run" technologies. Because of this, understanding how drought impacts these plants requires a more nuanced analysis than is presented in this paper, and as such nuclear generators are dropped from the sample. Solar thermal plants are also unique in their operation but are less water intensive and relatively rare. I also drop these plants from the sample.

Cooling I use the EIA-860, Schedule 6 form to identify the type of cooling used by plants: once through, recirculating, dry/hybrid, multiple. There are several caveats with this data however. First, only plants with over 100MW of capacity are required to fill out the form, though there is both non-compliance from some large plants and compliance from some smaller plants. Given the compliance rate is likely unrelated to drought conditions, this is not a threat to the internal validity of the analyses. Second, only plants with cooling systems are included. Since combustion turbines do not require cooling systems, plants with only combustion turbines would not appear in the data. As such I assume that all plants that are identified as primarily using combustion as the prime mover but are missing cooling information are dry cooled. Third, similar to fuel and prime mover types, a single plant may house multiple generators linked to multiple, different cooling systems. I identify the plant's main cooling system type as follows. If a plant only has one type of cooling system observed as operational it is assigned that type of cooling system. Of the plants with cooling system data, this covers 81%. If a plant is observed as having multiple types of cooling systems observed as operational at any point (eg. switching technologies over time or being dual equipped) then it is assigned the type "multiple". This accounts for 11% of the sample of plants with cooling data. Lastly, I repeat the process for plants that are associated with only retired cooling systems - those that only have one type are assigned that type (7%) while those with multiple are assigned to the "multiple" type group. The last concern is that the data is only available since 2009, though some plants that retired pre-2009 are still included. Since having multiple cooling types is relatively rare, I assume that plants do not switch technologies and assign plants their post-2009 cooling type as outlined above for all periods of the main analysis sample. The resulting distribution of cooling technologies over time is

Figure A2: Technology Mix Over Time



Note Figure plots total capacity associated with each of the four cooling technology groups over time for the sample of plants in ERCOT.

shown in Figure A2.

B.2 Market Data

Generation I use the EIA-923 form to identify the monthly plant level amount of energy generated. Monthly plant generation data is available from 2001 to 2023 at the plant by fuel by prime mover level. I measure total plant generation as the sum of generation from all technologies. Some plants are not consistently in the EIA-923 data, so end up with missing data values for generation when they are operational. After exploring news articles on a subset of these plants, it appears that this is reflective of plants being mothballed. Therefore, I assume that plants that are operational but missing generation data have zero generation and create an indicator for the plant being mothballed.

Prices and demand I use publicly available data from ERCOT for monthly measures of load and market clearing prices. For load, I sum the available hourly load data to get

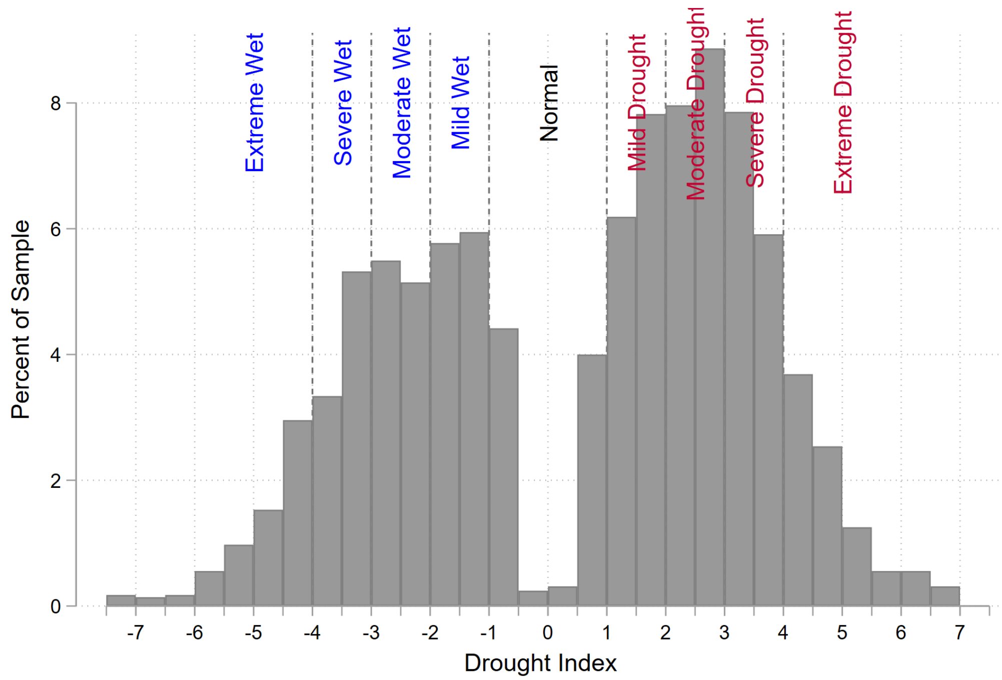
ERCOT wide total load (measured in MWh) for each month in my sample from 2002 to 2023. Market clearing prices (both DAM and RTM) are available in 15 minute intervals at both the hub level and the ERCOT wide average since 2010. I aggregate prices to the monthly level using a simple average of the 15 minute prices at both the hub and ERCOT wide level to measure the average wholesale market price. I also exploit the detailed nature of the price data to construct peak and non-peak prices at the hub and ERCOT level, defining peak prices as the average price from 1pm to 7pm and non-peak as the average from 7pm to 1pm. I combine the power plant data with the ERCOT market data using the plant coordinates to map each plant to its respective ERCOT hub.

B.3 Drought Data

I measure drought in this analysis with the Palmer Hydrologic Drought Index (PHDI). This index measure uses a long range of historic data on monthly precipitation, temperature, soil moisture storage and a water balance model to classify hydrologic drought, such as changes in reservoir levels or stream flows, into a scale from -10 to 10. The index values are structured to reflect common classifications of drought, with 0 being "normal" based on historic conditions, positive index values reflecting moist conditions and negative number reflecting dry condtions. The distribution of this index for my sample is shown in Figure A3. For ease of exposition, for my analysis I multiply the monthly PHDI observed in an area by negative one, so that more positive numbers mean more severe drought. Monthly estimates of the PHDI are defined for climatologically similar areas across the US, with 10 of these climate divisions defined in Texas. These devisions are predefined by NOAA (Voase et al., 2014). Additionally, the PHDI can be classified into broader categories of drought following standardized cutoff levels: no drought [-10, 1), mild [1,2), moderate [2,3), severe [3,4), and extreme [4,10).

I use the PHDI measure as opposed to alternative measures such as precipitation or the Palmer Drought Severity Index since the PHDI is structured to capture longer run hydrologic changes, and is available since 1895. The hydrologic change aspect is important for my analysis, since power plants are most likely affected by changes in reservoir levels or stream flows that would occur only after longer periods of drought instead of short term

Figure A3: Histogram of PHDI Over Sample



Note Figure plots histogram of scaled PHDI measures for climate divisions in Texas over 2000 to 2023. Dashed vertical lines indicate breaks in the discrete categorization of the PHDI, as defined by NOAA.

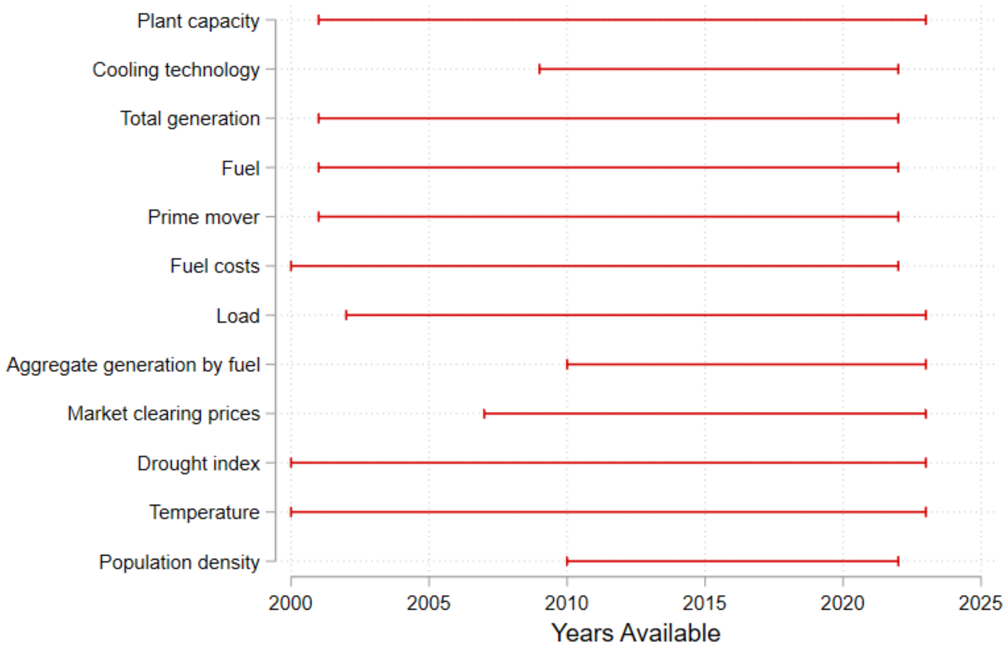
shocks. Having the data for a long time span is also important, since it allows me to consider the local drought conditions when plants were constructed.

I also use precipitation to measure differences in long run average water availability. The PHDI is unable to measure this long-term difference since it measures local drought, which is a deviation from normal conditions, mechanically requiring standardization of long-run average conditions across space. This means that the average PHDI for all climate divisions converges towards zero (ie. "normal" conditions) as the time horizon increases, and so the PHDI misses that some areas are wetter during "normal" times than others.

B.4 Other Data Sources

I link the power plants in my sample to several other environmental and market variables. First, I use the coordinates of plants to link them to local environmental characteristics such as average solar irradience, wind speed, and monthly temperature. Solar irradience and wind speed are time invariant categorical data produced by the National Renewable Energy

Figure A4: Data Availability



Note Figure plots the range of time that key variables are available in the raw datasets.

Laboratory covering the US, and are important determinants of the productivity of solar and wind generators. County temperatures are obtained from NOAA's GHCNCAMS Gridded 2m Temperature data.

I also link plants to the appropriate county's annual population density, which is likely correlated with energy demand, transmission costs, and siting costs. The county level population density from the US Census is only available after 2010, so I use linear extrapolation to estimate the population densities from 2001 through 2009.

A visual representation of the available time horizons for key data is shown in Figure A4.

C Spot Market Supplementary Figures and Tables

I addition to main analyses, I also examine several alternative specifications to look at the impact of drought on generation and prices, the results of which are summarized here.

Impact on Capacity Constrained I examine the impact of drought on the likelihood that power plants are producing at capacity, using the same framework as Equation 1, in Table A5. For low water use plants I find a positive, though statistically insignificant, relationship between local drought and the probability a plant is capacity constrained and a negative relationship with non-local drought. For dry cooled plants there appears to be no clear relationship between being constrained and drought. There is insufficient data for estimation of the relationship for high water use plants.
The results provide suggestive evidence that drought may change the likelihood low water use plants hit their capacity constraint.

Alternative drought measures There are many possible ways to measure variations in water supplies and I test several alternatives.

I test measuring drought with climate division monthly total precipitation, standardized at the division level. The results for generation, shown in Table A1 show a statistically significant increase in generation from low water use plants in response to a one standard deviation reduction in non-local precipitation, but otherwise generally negligible and imprecise impacts for other thermal plants.[33] Non-thermal generators show increases in production with reductions in precipitation both locally and non-locally. Table A2 shows that when measuring precipitation in both levels and deviations there are negligible impacts on prices. The limited response when measuring drought with precipitation is explainable by the fact that precipitation shocks are relatively short run and unlikely to significantly impact plant water supplies.

I also examine the effect of drought duration, measured as continuous months in at least moderate drought. I find that a one month increase in either local or non-local drought

[33]For comparison, the general categorizations of the PHDI align so that a one standard deviation in PHDI measures corresponds to the cutoff between moderate and severe, while two standard deviations approximately corresponds to the cutoff between severe and extreme.

duration has negligible impacts on production quantities (Tables A3 and A4). However, Table A5 shows small but statistically significant increases in prices of around 1%. The 75th percentile of drought duration in the data is about 13 months, leading to an economically meaningful price increase for long droughts.

I additionally estimate the effect of the number of climate divisions that are in at least severe drought on prices. The results in Figure A6 show that prices increase when a majority of climate divisions experience severe drought. In contrast, when I focus on prices as a function of the worst drought level in the market, I find little effect with drought severity as shown in Figure A7.

These results suggest that prices are primarily influenced by the share of the market that is exposed to drought, more so than the severity of drought in any one location.

Sample selection In the main analyses, the sample I use covers all operating utility-owned power plants in ERCOT since 2010. I examine the robustness of my results to focusing on some subsets of observations.

I first vary the set of plants selected. In Figure A8 I repeat my analyses including non-utility owned power plants, and find similar results as the main analysis for all but dry cooled plants. Local drought now adversely affects these plants, suggesting plants that produce electricity for non-market reasons experience reductions in demand for that energy during drought conditions. Similarly, in Figure A9 I repeat the main analyses excluding combined heat and power plants which also produce electricity for non-market (heating) reasons. The results are again similar for all technologies but dry cooled plants, with local drought again reducing their share of capacity used.

I next vary the range of time used in the analyses. In Figure A10 and Figure A11, I repeat the main analyses excluding observations from June through September, since transmission congestion is more likely in summer when demand is highest. I find similar results as the main analyses, though the changes for dry cooled generation and prices are attenuated. The reduced impact likely reflects that during low demand in winter, there are more low cost plants available to substitute for the reduced high water use generation.

In total, changing the sample selection process appears to have a limited impact on the main

Figure A5: Drought Effect on Probability Plant is Capacity Constrained

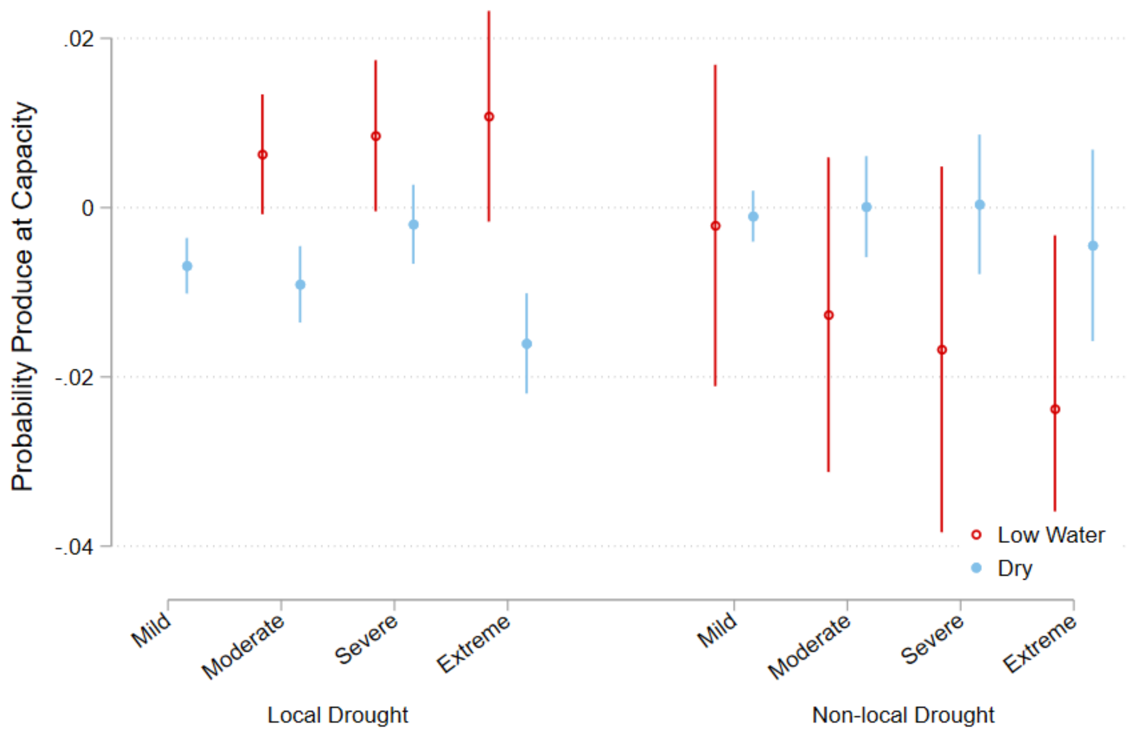


Figure plots marginal effect estimates for the impact of local and non-local drought on the probability a plant is producing at capacity. The analyses are run separately for each of the four technology groups shown in the legend. Non-drought conditions are the omitted category for both local and non-local drought. Standard errors are clustered at the climate division level. 95% confidence intervals are denoted by the vertical bars.

takeaways of the analysis.

Table A1: Precipitation Deviation Effect on Share of Capacity Used

	(1) High Water	(2) Low water	(3) Dry	(4) Non-thermal
Local precipitation	0.0051**	-0.0018	0.0037**	-0.0037***
	(0.0026)	(0.0062)	(0.0015)	(0.0010)
Non-local precipitation	-0.0025	0.0143***	0.0002	-0.0116***
	(0.0020)	(0.0032)	(0.0026)	(0.0009)
Observations	2,415	9,370	14,602	25,256

Table presents marginal effect estimates for the impact of local and non-local drought on the share of capacity used. Drought is measured with deviations from normal precipitation levels. The analyses are run separately for each of the four technology types. Standard errors are clustered at the climate division level and shown in parentheses.

Table A2: Precipitation Deviation Effect on Prices

	(1) Levels	(2) Standard deviations
Local precipitation	0.0001	0.0028
	(0.0057)	(0.0115)
Non-local average precipitation	-0.0040	-0.0085
	(0.0189)	(0.0369)
R-squared	0.590	0.590
Observations	53,261	53,261

Table presents marginal effect estimates for the impact of local and non-local drought on wholesale prices. Drought is measured with deviations from normal precipitation levels. The analyses are run separately for each of the three prices. Standard errors are clustered at the plant and month-of-sample level and shown in parentheses.

Table A3: Drought Duration Effect on Share of Capacity Used

	(1) High water	(2) Low water	(3) Dry	(4) Non-thermal
Local drought	-0.000	0.001***	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Non-local drought	-0.000	0.000	0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,269	9,022	14,312	24,283

Table presents marginal effect estimates for the impact of local and non-local drought duration (in months) on the share of capacity used. The analyses are run separately for each of the four technology types. Non-drought conditions are the omitted category for both local and non-local drought. Standard errors are clustered at the climate division level and shown in parentheses.

Table A4: Drought Duration Effect on Probability Plant is Running

	(1) High water	(2) Low water	(3) Dry	(4) Non-thermal
Local drought	-0.001	0.001***	0.002	0.000
	(0.002)	(0.000)	(0.002)	(0.000)
Non-local drought	-0.001	-0.000	0.005	0.000
	(0.001)	(0.000)	(0.003)	(0.000)
Observations	2,269	9,022	14,312	24,249

Table presents marginal effect estimates for the impact of local and non-local drought duration (in months) on the probability a plant is operating. The analyses are run separately for each of the four technology types. Standard errors are clustered at the climate division level and shown in parentheses.

Table A5: Drought Duration Effect on Prices

	(1) Avgerage	(2) Non-peak	(3) Peak
Local drought duration	0.008***	0.011***	0.005**
	(0.002)	(0.002)	(0.002)
Non-local drought duration	0.009***	0.012***	0.006***
	(0.002)	(0.003)	(0.002)
Observations	51,501	35,306	17,257

Table presents coefficient estimates for the impact of local and non-local drought duration (in months) on wholesale prices. The analyses are run separately for each of the three price measures. Standard errors are clustered at the climate division level and shown in parentheses.

Figure A6: Number of Division in Drought Effect on Prices

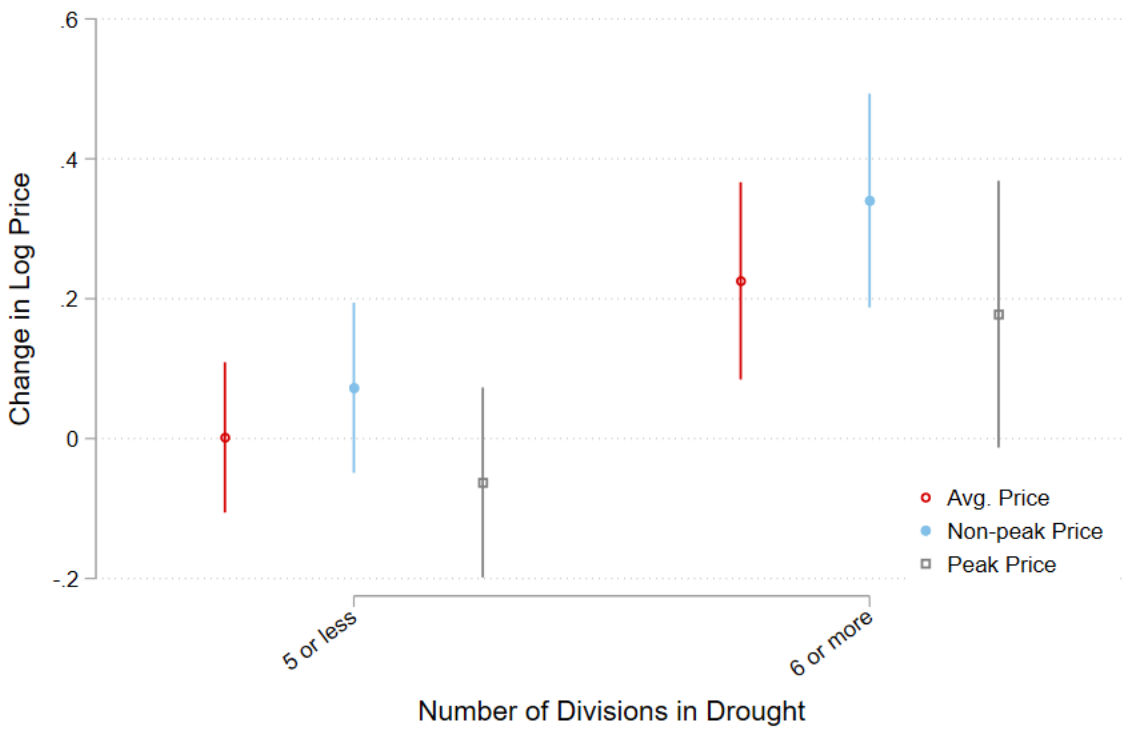


Figure plots coefficient estimates for the impact of the number of climate divisions experiencing at least severe drought on wholesale prices. The analysis is run separately for each of the three prices shown in the legend. Zero climate divisions in severe drought is the omitted category. Standard errors are clustered at the plant and month-of-sample level. 95% confidence intervals are denoted by the vertical bars.

Figure A7: Worst Drought in Market Effect on Prices

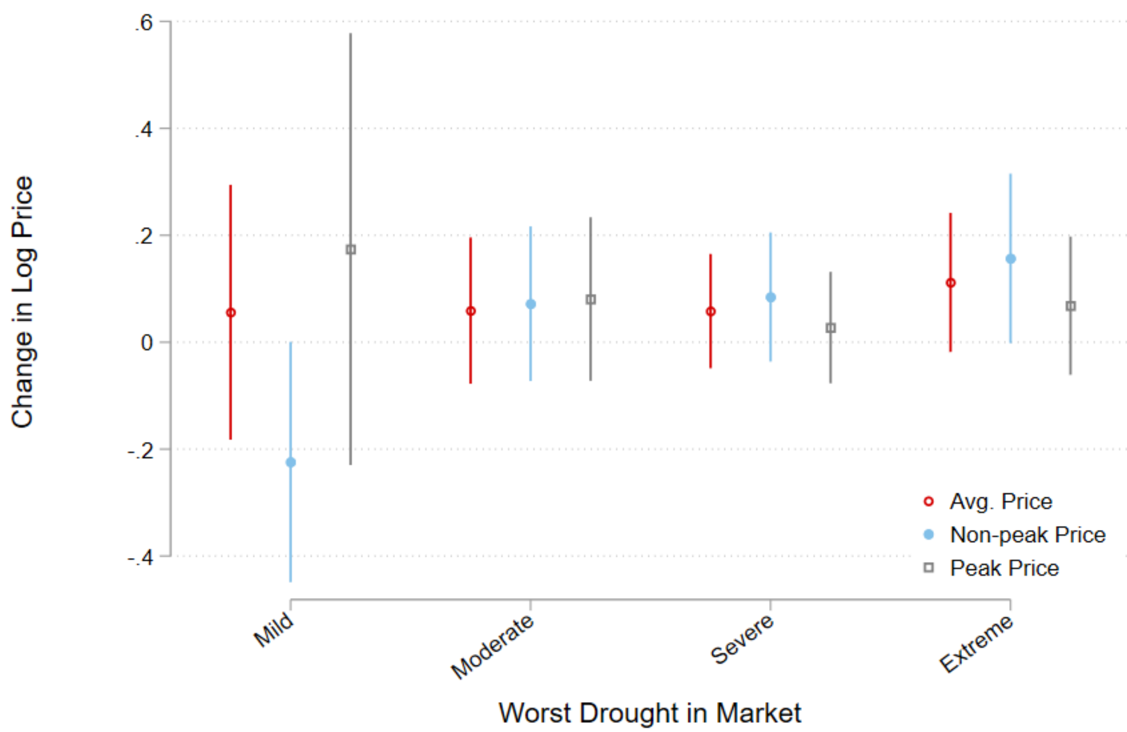


Figure plots coefficient estimates for the impact of the worst drought in the market on wholesale prices. The analysis is run separately for each of the three prices shown in the legend. Zero climate divisions in severe drought is the omitted category. Standard errors are clustered at the plant and month-of-sample level. 95% confidence intervals are denoted by the vertical bars.

Figure A8: Production Response of Utility Plants

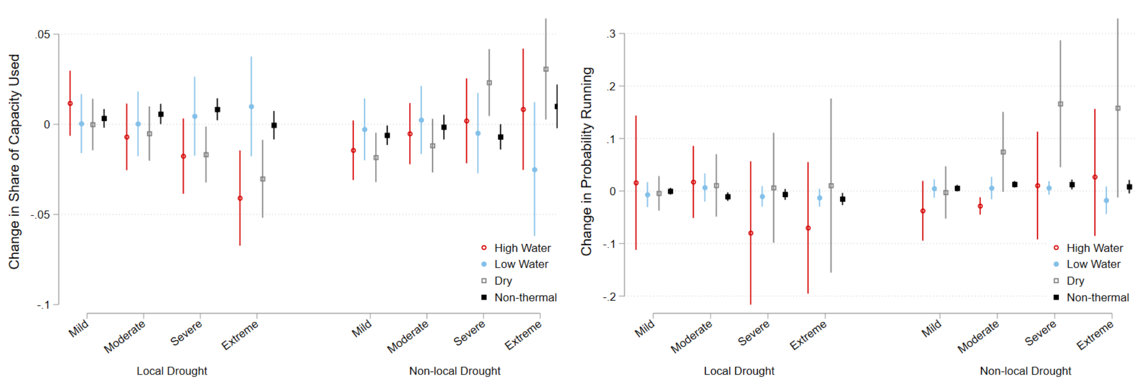


Figure plots marginal effect estimates for the impact of local and non-local drought on the share of capacity used and the probability a plant is running, for the subset of plants owned by a utility. The analyses are run separately for each of the four technology groups shown in the legend. Non-drought conditions are the omitted category for both local and non-local drought. Standard errors are clustered at the climate division level. 95% confidence intervals are denoted by the vertical bars.

Figure A9: Production Response of Non-cogeneration Plants

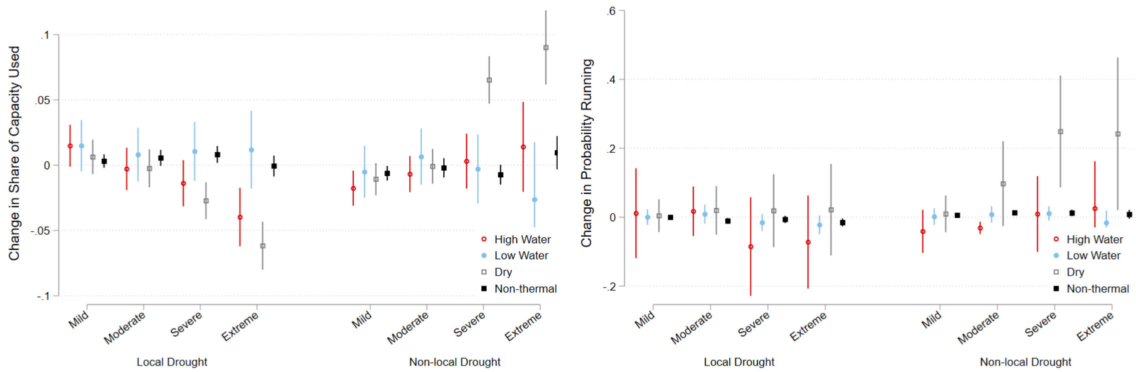


Figure plots marginal effect estimates for the impact of local and non-local drought on the share of capacity used and the probability a plant is running, for the subset of plants that are not combined heat and power plants. The analyses are run separately for each of the four technology groups shown in the legend. Non-drought conditions are the omitted category for both local and non-local drought. Standard errors are clustered at the climate division level. 95% confidence intervals are denoted by the vertical bars.

Figure A10: Production Response During Non-Summer Months

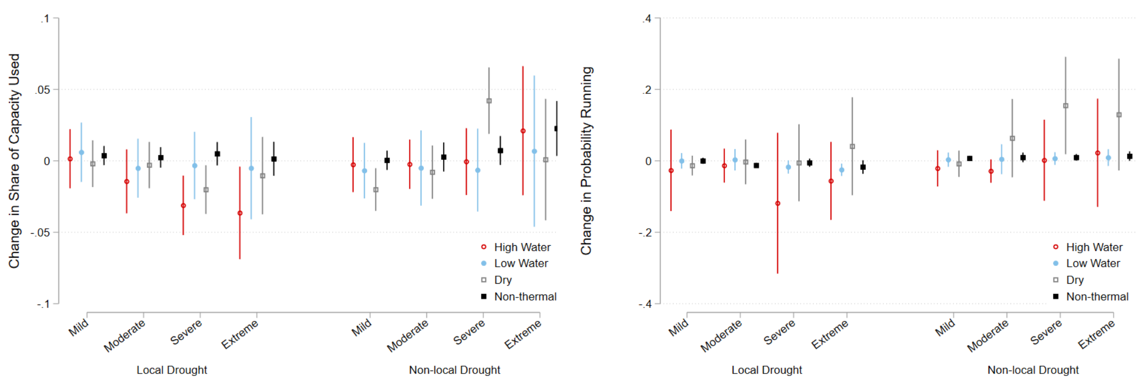


Figure plots marginal effect estimates for the impact of local and non-local drought on the share of capacity used and the probability a plant is running, for the subset of observations not occuring June through September. The analyses are run separately for each of the four technology groups shown in the legend. Non-drought conditions are the omitted category for both local and non-local drought. Standard errors are clustered at the climate division level. 95% confidence intervals are denoted by the vertical bars.

Figure A11: Drought Effect on Non-Summer Wholesale Prices

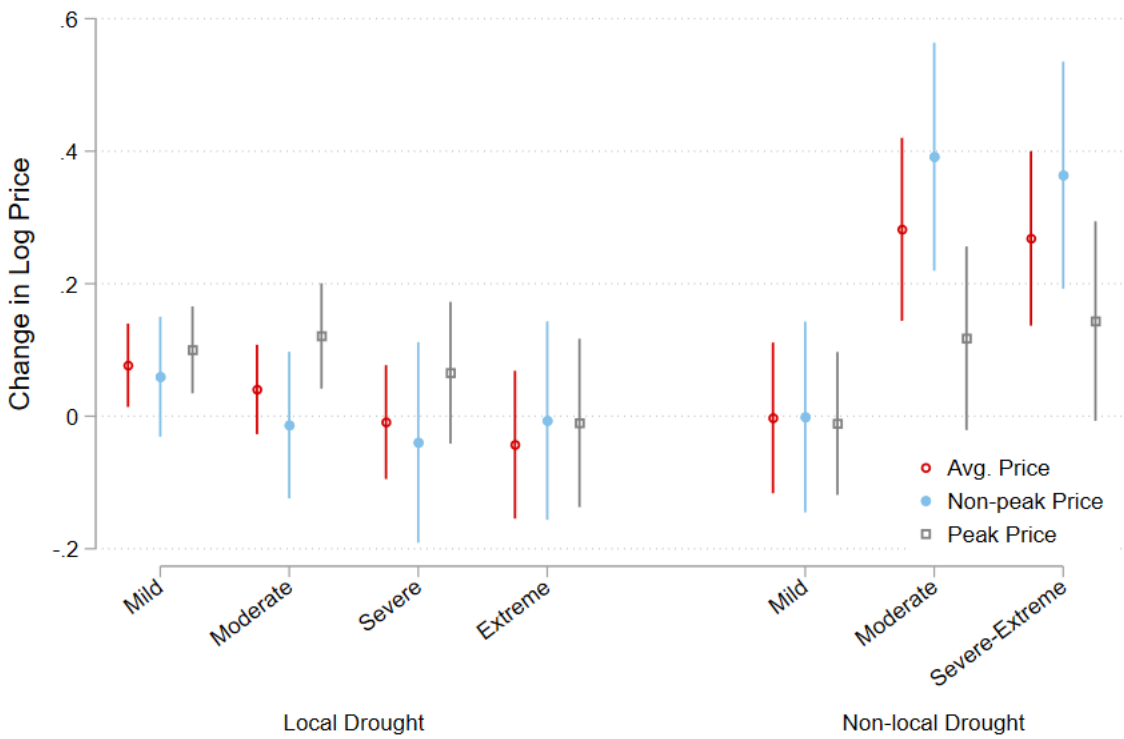


Figure plots coefficient estimates for the impact of local and non-local drought on wholesale prices in non-summer months. The analysis is run separately for each of the three prices shown in the legend. Non-drought conditions are the omitted category for both local and non-local drought. Standard errors are clustered at the plant and month-of-sample level. 95% confidence intervals are denoted by the vertical bars.

D Investment Supplementary Figures and Tables

I addition to the main analyses, I also examine alternative measures of investment and drought with additional analyses, the results of which are summarized here.

Conditional correlation with precipitation I quantify the relationship shown in Figure 6 with OLS regression in Table A6. I condition the correlations on continuous measures of average population density and total generating capacity and categorical variables for state, average solar irradiance and average wind speed. The results show that wetter areas have a higher share of capacity in high water use technologies and relatively less investment in non-thermals, with both coefficients being marginally statistically significant at standard levels.

Conditional on key environmental variables, water availability is positively correlated with high water use technologies.

Cancellation of Planned Plant I also consider the outcome of whether a planned plant is subsequently canceled as a function of drought. The data used for this analysis is only available since 2015 and does not contain cooling information, so I am only able to categorize observations as "likely dry", "likely non-dry", and "non-thermal".[34] I regress an indicator for cancellation on the interactions of these classifications with the average drought between 2000 and 2023. The results, shown in Table A8, find that a one standard deviation worse previous drought relatively decreases the likelihood non-thermal plants are canceled.

The analysis provides suggestive evidence that drought may also impact investment before plants are constructed.

Climate Division Panel As an alternative to plant level analyses, I construct a climate division by decade panel. With this data set I examine whether drought impacts whether there is any investment in a location at all. Table A9 shows the estimated change in both total capacity and total new capacity investment as a function of standardized previous

[34] I make this categorization based on information about the prime mover. Thermal combustion is classified as "likely dry", while non-combustion thermals are classified as "likely non-dry".

drought conditions. The results show minimal differences when using either level or log changes across both possible outcome variables.

I also examine investment by technology as the share of new capacity constructed in a location that uses the respective technology. The results, shown in Table A10 align in direction of coefficient with the main results but are statistically insignificant. A one standard deviation worse drought in the prior decade is associated with a 1 percentage point reduction in the share of new capacity that is high water use, which over a 7 percentage point base is reasonably large. For low water use, dry, and non-thermals, the table shows statistically insignificant increases in capacity share.

In aggregate, drought does not seem to be related to total investment but there is suggestive evidence that the plant level results hold with respect to technology specific investment.

Natural Gas Plants A potential concern is that structural change in electricity markets due to the proliferation of cheap natural gas is driving a spurious correlation with drought. To examine this, in Table A11 I repeat the main analysis for technology choice at investment and mothballing using only natural gas fueled plants. There is insufficient sample variation to examine retirement. For the probability a plant uses a given technology, I find similar results as the main analysis, with drought reducing investment in high water use plants by 4.4 percentage points and increasing investment for dry by 2.1 percentage points. The results for mothballing are also similar to the main results.

Overall, it appears that the main results are robust to focusing only on natural gas plants.

Table A6: Conditional Correlations with Drought

	(1) High water	(2) Low water	(3) Dry	(4) Non-thermal
Average precipitation	0.068*	0.028	0.034	-0.067*
	(0.039)	(0.033)	(0.042)	(0.039)
Sample mean	0.107	0.286	0.254	0.353
Observations	328	328	328	328

Table presents conditional correlations between average precipitation since 1980 and the share of capacity using each technology type as of 2023. The unit of observation in a climate division in January 2023. Controls include continuous measures of average population density and total generating capacity and categorical variables for state, average solar irradience and average wind speed. Analysis is run separately for each thermal technology. The sample average share of capacity for each technology is shown at bottom. Heteroskedastic robust standard errors are shown in parentheses.

Table A7: Technology Choice at Investment Controlling Future Drought

	(1) High Water	(2) Low Water	(3) Dry
Mean PHDI 10 years before	-0.048*	0.034	0.022
	(0.028)	(0.026)	(0.017)
Mean PHDI 10 years after	-0.004	0.003	-0.007
	(0.028)	(0.029)	(0.014)
Mean	0.31	0.54	0.15
Observations	420,203	519,241	572,027

Table presents correlations between standardized average previous drought conditions and the probability that an operating thermal plant is mothballed. Analysis is run separately for each thermal technology. Observations are weighted by plant capacity, winsorized at the 90th percentile. The sample average probability of being mothballed is shown at bottom. Standard errors are shown in parentheses and clustered at the climate division level.

Table A8: Probability Planned Investment is Canceled

	(1) Canceled Indicator
Mean PHDI since 2000	0.038
	(0.041)
Combustion indicator	0.074*
	(0.045)
Combustion × PHDI	-0.021
	(0.044)
Non-TE indicator	-0.121***
	(0.034)
Non-TE × PHDI	-0.082***
	(0.028)
Cancel rate TE, non-combust	0.262
Cancel rate combustion	0.099
Cancel rate non-TE	0.292

Table presents correlations between drought between 2000 and 2023 and the probability a planned capacity investment is canceled by 2023. The sample average probability of cancellation by technology type is shown at the bottom. Standard errors are shown in parentheses and clustered at the climate division level.

Table A9: Total Investment in Climate Division

	(1) Total	(2) ln(Total)	(3) New	(4) ln(New)
Previous decade average drought	6,364.594	-0.021	3,537.085	-0.085
	(9,464.744)	(0.026)	(5,585.614)	(0.079)
Sample mean	469,658	546,101	96,605	166,254
Observations	1,986	1,708	1,986	1,154

Table presents correlations between average drought in the period before and capacity in a climate division. Outcome variables denoted by column titles are the total amount of capacity (1), the inverse hyperbolic sine of total capacity (2), the total amount of new capacity (3), and the inverse hyperbolic sine of the total amount of new capacity (4). Observation is at the climate division by decade level. Analysis conditions on categorical variables for climate division and decade. Heteroskedastic standard errors are shown in parentheses.

Table A10: New Investment Share by Technology

	(1) High water	(2) Low water	(3) Dry	(4) Non-thermal
Average drought	-0.011	0.003	0.007	0.011
	(0.009)	(0.012)	(0.013)	(0.008)
Sample mean	0.070	0.215	0.464	0.251
Observations	1,154	1,154	1,154	1,154

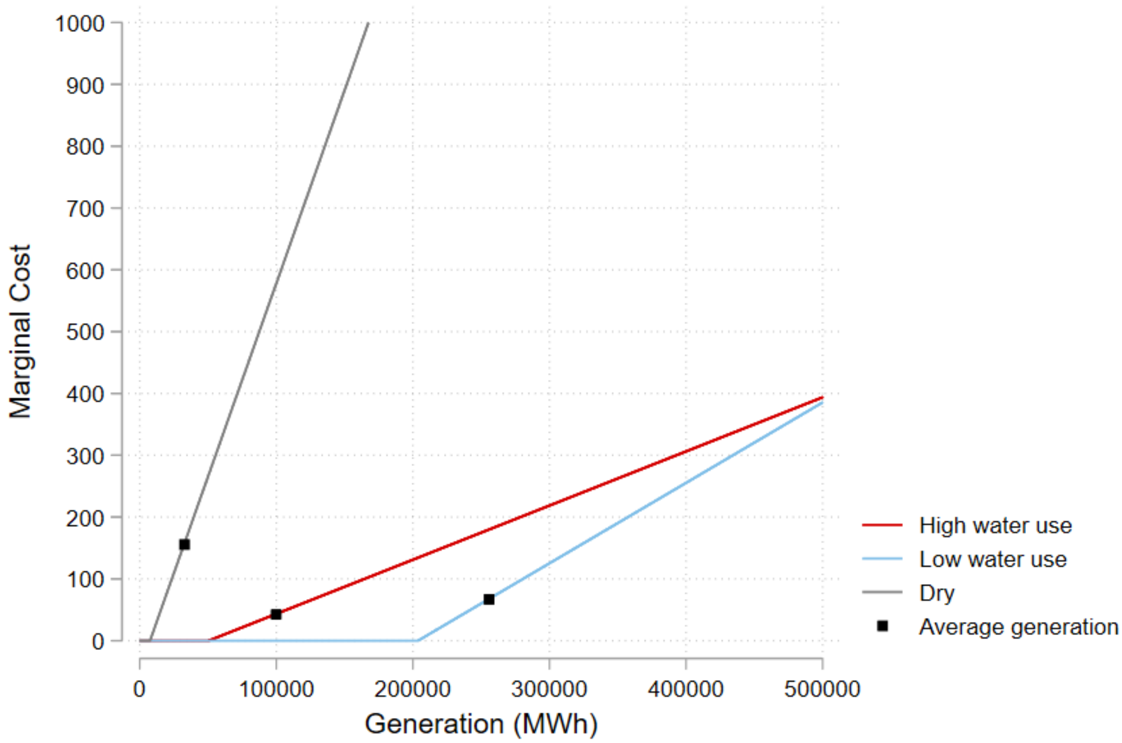
Table presents correlations between standardized average drought in the period before and share of new capacity in a climate division that is each technology type. Technology type is denoted by column titles. Observation is at the climate division by decade level. Analysis conditions on a continous measure of total capacity in the location and categorical variables for climate division and decade. Heteroskedastic standard errors are shown in parentheses.

Table A11: Investment Response for Natural Gas

	High Water Use	Low Water Use	Dry
Panel A: Probability plant uses technology			
$\overline{\text{PHDI}}$ 10 years before construction	-0.041	0.024	0.045*
	(0.037)	(0.033)	(0.023)
Mean Outcome	0.196	0.482	0.322
Observations	373	896	961
Panel B: Probability plant mothballed			
$\overline{\text{PHDI}}$ 10-1 years before	0.041***	0.030***	-0.006
	(0.013)	(0.010)	(0.005)
Mild PHDI last year	-0.000	-0.012**	-0.000
	(0.007)	(0.005)	(0.003)
Moderate PHDI last year	0.019	-0.008	-0.005
	(0.012)	(0.006)	(0.004)
Severe PHDI last year	0.018	-0.001	-0.001
	(0.019)	(0.009)	(0.006)
Extreme PHDI last year	0.052	-0.004	-0.004
	(0.044)	(0.009)	(0.007)
Mean Outcome	0.083	0.042	0.040
Observations	15,823	34,692	221,991

Table presents correlations between average drought in the ten years before and after a thermal plant is constructed and the probability of using a technology type. Analysis is run separately by technology conditional on fuel type. Observations are weighted by plant capacity, winsorized at the 90th percentile. Standard errors are shown in parentheses and clustered at the climate division level.

Figure A12: Estimated Marginal Costs Curves



Note Figure plots estimated marginal cost curves for each thermal technology type. The black square indicates the estimated marginal cost at average production.

Table A12: Seasonality of State Variables

	Time and location	Full
Temperature	.9687154	.9958103
Drought	.7292544	.9541526
Non-thermal productivity	.7442725	.8317598
Demand	.9416667	.9759566
Price	.2175221	.5877579

Table presents R^2 estimates from linear regressions using the variable shown on the left as the outcome variable. The first column includes month-of-year dummies and a linear year trend fully interacted with climate division dummies. The second column reflects the specifications denoted in Equations 11-15. Analyses use either a climate division level panel or market wide time-series for estimation.