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. This paper shows that while short run drought shocks can adversely affect high water-use power plants, the subsequent increase in wholesale prices is mitigated by long run changes in the mixture of generating technologies. I first estimate the short run impact of drought shocks on the Texas electricity market (ERCOT), showing that high water use plants reduce production with direct drought exposure while dry cooled power plants substitute for the lost generation. This change in generation is associated with a 30% increase in wholesale prices. I also provide suggestive evidence that firms adapt to future drought risk by shifting investment towards less water-intensive technologies. I then estimate a model of investment and production in electricity markets which is novel in incorporating drought as a determinant of production costs. I find that endogenous investment significantly reduces the impact of drought on electricity markets. The findings from this paper are informative for several policy areas, from optimal investment in renewable technologies to environmental inequities arising from spatial pollution exposure.

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1 Introduction

Climate change is expected to exacerbate drought conditions, making drought events both more frequent and more severe (USGS, 2023). 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, potentially less efficient, plants increasing production in response to the new market equilibrium. In the long run, firms may adapt to increased drought risk 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, using these historical relationships between electricity production and drought, I estimate an empirical model which allows me 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 technology mix being endogenous to future drought conditions. The counter-

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

factual analyses predict that under more severe future drought conditions the equilibrium technology mix shifts towards non-thermal (ie. wind and solar) plants. This change in the technology mix mitigates some of the direct impacts of drought on the market.

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 quanty 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.

I next develop a structural model of investment and production to understand how climate change will impact future energy supplies, accounting for adaptation of the technology mix. While the first set of reduced form analyses show that drought shocks impact electricity markets, it is not prudent to extrapolate these results to future climate scenarios since they are dependent on the technology mix which, as the second set of analyses shows,

[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.

is related to long term drought conditions. Instead, using the structural model allows me to explicitly accommodate endogenous adaptation of the technology mix for counterfactual analyses of drought conditions under climate change.

In the model, 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 $30/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), investment shifts away from high water use plants towards non-thermal plants, with larger changes under the more severe climate change scenario. For the high drought severity scenario, the share of capacity that is high water use drops from 8.6% to 1.6%, while the share of capacity that is non-thermal grows from 42% to 50%. Due to the growth in non-thermal generation, which is assumed to have no operating costs, steady state wholesale prices decline relative to baseline, while also helping mitigate the price impact of a drought shock. However, due to the increase in market share of non-thermal generation, low aggregate productivity shocks for non-thermal plants result in larger price spikes, since during these shocks the only available substitutes are high cost dry plants.

My paper provides the first analysis that accounts for endogenous technological adaptation when estimating the impact of drought on electricity generation. This paper therefore contributes to the large literature on the consequences of climate change.[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 the generating technologies do not adapt to changes in drought. My analysis bridges these existing works by providing both novel evidence that technological adaptation

[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).

is important, and new quantification of the supply side impact of climate change explicitly accommodating 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.

The results from the analyses in this paper have important implications for grid stability, end consumer prices, and total emissions. First, after accounting for adaptive investment the direct effect from climate change-driven drought is relatively low. Additionally, while the counterfactual analyses show the shift towards non-thermal technologies helps mitigate the price impact from drought, the overall price volatility is higher due to fluctuations in non-thermal production. However, the growth of non-thermals is also associated with changes in emissions from the grid, with a back-of-the-envelope calculation suggesting a 12% decline in CO_2 emissions per kWh. The net welfare impact therefore is ambiguous, with lower prices and emissions being welfare improving, but higher price volatility potentially being welfare reducing.

2 Generation Technologies and ERCOT Overview

2.1 Comparison of Alternative Generation Technologies

There are many different technologies used to generate electricity, where each technology is subject to trade-offs between dispatchability, heat rate (i.e. plant efficiency), and water use. Dispatchability reflects a plant's ability to respond to changes in demand. A plant's heat rate measures the plant's efficiency as the amount of energy required to produce 1Kwh of electricity. The remainder of this section will detail these trade-offs further.

The different generating technologies fall into one of two categories: thermal and non-thermal. Non-thermal technologies, such as hydroelectric, wind, and photovoltaic generators, do not produce electricity through conversion of heat energy and are generally non-dispatchable generators. Thermal technologies on the other hand use heat energy in the form of steam or gas to spin a turbine and produce electricity allowing them to be more responsive to demand. Within thermal generators, there is variation in dispatchability and heat rates based on what is used to spin the turbine, called the prime mover. Generally, the most dispatchable technologies (combustion generators) have higher heat rates (lower efficiency) as well (EIA, 2023).

How a thermal plant is cooled determines the plant's water needs and impacts the plant's heat rate. Once through cooled systems (from here on called high water use plants) pull water from a nearby water source to cool the steam or gas used in the generation process, 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, recirculating systems (low water use plants) reuse the cooling water, which reduces the water withdrawn but increases the amount of energy needed to run the system, since the water mush be cooled back down before reuse. This process can reduce a plant's efficiency by 2-5% (World Nuclear Association, 2020). Lastly, plants may be convective (dry) cooled instead, though this process is even more energy intensive (EPRI and Commission, 2002). Figure 1 shows that the differences in water withdrawals across technologies are significant.

For this project, I am characterize a plant's water needs as the amount of water withdrawn to produce electricity. It is relevant to note that water withdrawn does not equate to water consumed. High water use plants withdraw large volumes but return the majority of that water to the source, in contrast with low water use plants which consume almost all of the water withdrawn (see Figure A11 in the Appendix). The differences in consumption are important for water management and downstream users, but more detailed consideration of this aspect is beyond the scope of this paper. 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.

Figure 1: Water Withdrawals by Technology

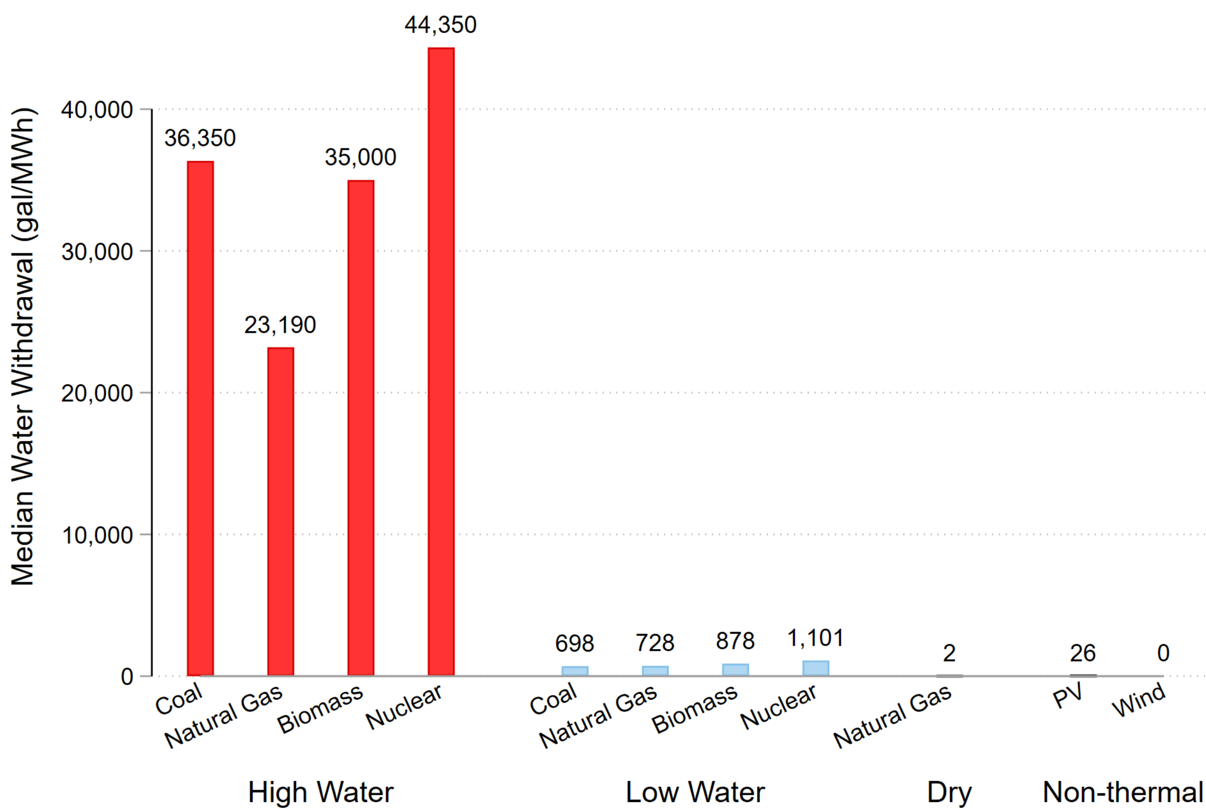


Figure plots the median volume of water withdrawn per Kwh of electricity produced. The x-axis categories disaggregate first by cooling technology and then by fuel type. Values are collected from Macknick et al. (2011).

2.2 ERCOT Market Structure Overview

For several analyses I focus on the Electricity Reliability Council of Texas (ERCOT), which has several key features making it an attractive setting. First, ERCOT serves 26 million consumers across the majority of Texas, making it a large market both in terms of transaction volume and spatial area. Second, it is isolated from other grids[4], limiting the impact of imports or shocks to systems outside of Texas. Third, within ERCOT generation from hydroelectric sources accounts for less than 0.1% of total generation, which is useful for the analysis since it rules out potential indirect effects of drought on thermal generation through equilibrium impacts due to changes in hydroelectric generation.

The ERCOT wholesale electricity market was restructured in 1999 to be competitive, and an external independent market monitor is tasked with overseeing that the market stays competitive ($HHI = 1,020$ in 2022).[5] In the market, generating firms sell electricity to the grid or directly to utilities in the bilateral forward market, the day ahead market (DAM), and the real-time market. While the majority of transactions in the whole sale market occur in the forward market, the prices from the DAM are important for shaping firms' expectations over future prices, leading to a high correlation of prices among the three markets (ERCOT IMM, 2023).

In the DAM, how much plants produce and the price they receive are determined by their merit order ranking. In short, generators are operated in order of ascending price, meaning the cheapest to run generators are used first, while the most expensive generators are used last. The price setting plant is the marginal plant that fulfills demand, with all plants receiving a common price. This means that in periods of low demand, the marginal plant is relatively low cost (front of the line) leading to a lower wholesale price. In periods of high demand, the marginal plant is relatively high cost (back of the line) leading to a higher wholesale price.

Within the DAM, there are also smaller "markets" which occur as a result of phys-

[4]There are only 5 interconnection points with other grids, which can contribute up to 1,220 MW of capacity, or less than 1% of total capacity.

[5]While the market is considered to perform competitively, there is evidence that there is some room for strategic behavior (ERCOT IMM, 2023; Woerman, 2023).

ical 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, the hub price equals the market average price, but during congested periods the hub price may differ from the market average price. This dynamic is important for the subsequent analyses since it means that within ERCOT there is cross sectional variation in the price that plants receive for electricity generation based on the hub where the plant is located.

3 Drought in a Simplified Market Framework

This section presents a simplified framework to outline how drought could impact electricity markets through both spot market generation and endogenous investment. I outline a highly stylized electricity market, which I use to identify several testable hypotheses that are then used to guide the subsequent analyses of the paper. The framework shows that drought shocks in the spot market result in higher equilibrium prices as generation shifts from high water use plants to lower water use plants. The subsequent price increase results in investment in lower water use capacity, which can in turn mitigate the spot market shock.

3.1 Simplified Two-Plant Electricity Market Framework

Consider a competitive market with two power plants, one a high water use (HW) plant and the other a low water use (LW) plant. The plants produce electricity to meet an inelastic demand D in a spot market. Each plant has a linear supply curve, but capacity constraints limit the maximum amount of energy they can produce to K_i. Assume that the HW plant has a lower marginal cost of production in absence of drought. Lastly, assume that plants can costlessly invest in new capacity, increasing the maximum amount they can produce.

This simplified market in absence of drought is graphically depicted in Panel A of Figure 2. The blue and red lines show the plant level supply curve for the HW and LW plants respectively, which aggregate up to the market level supply curve shown with the black dashed line. The market clears where the inelastic demand level intersects the market

Figure 2: Production Response of Stylized Market to Drought Shocks

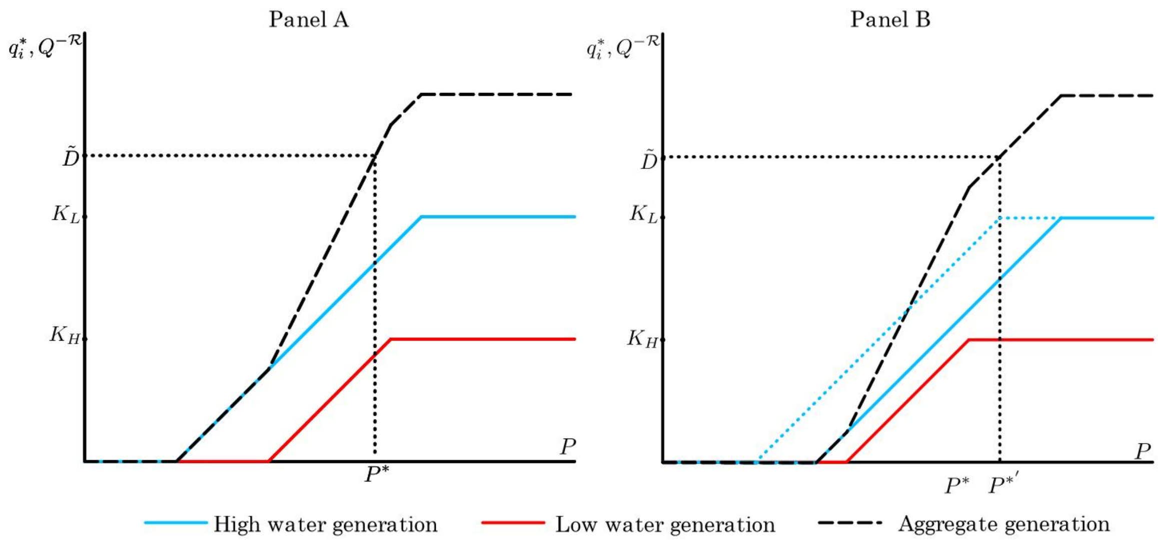


Figure shows stylized example of drought shock impact on plant level supply curves and wholesale prices.

supply, resulting in the market clearing price P^*.

3.2 Effect of Drought Shock on Simplified Spot Market

Now imagine that there is a drought which increases the marginal costs for the HW plant only, shifting the plant's supply curve out as shown in Panel B of Figure 2. For the same fixed demand level, the new market equilibrium will result in the HW plant producing less relative to the non-drought case. The reductions in supply from the HW plant are made up for by an increase in production by the higher cost LW plant. This shift in production between affected and unaffected plants leads to the first hypothesis:

Hypothesis 1: *A local drought shock will (weakly) reduce generation from affected HW plants, and (weakly) increase generation from unaffected plants in the market.*

To fully meet demand, the new equilibrium with drought also results in a higher market clearing price, $P^{*'}$. This is due to a combination of drought increasing the production costs of the HW plant and a shift of generation towards the LW plant. This is the second hypothesis.

Hypothesis 2: *A local drought shock will (weakly) increase the market clearing price.*

It is important to note that the magnitude of any change in generation or prices will largely depend on the *relative* locations of the price setting plant's and the substituting plant's supply curves on the graph. For example, in the stylized example presented here if the HW plant's supply curve is significantly lower than the LW plant's so that the HW plant is producing at capacity both absent and during the drought shock, then the price setting plant will always be the LW plant. There would therefore be no price shock at all. If instead the drought shock shifted the HW plant's supply curve out beyond the LW supply curve, it would be the price setting plant leading to a significant price increase. In a market with more plants, this dynamic scales up so that having more unaffected plants with similar supply curves to the baseline price setting plants allows the market to offset the drought cost shock with minimal price consequences. On the other hand, having substitute plants with very different supply curves from the price setting plants would lead to a large price response.

Hypothesis 3: *The effect of a local drought shock will depend on relative distance between the supply curves of the price setting plants and substitute plants.*

3.3 Effect of Drought Shock on Investment in Simplified Market

Now imagine that the example plants believe the drought shock in Figure 2 is a permanent change, so that the HW plant will always face higher production costs. Under the resulting equilibrium, repeated in Panel A of Figure 3, the LW plant would like to produce more but is capacity constrained. With costless investment, the LW plant would increase its capacity, leading to the new equilibrium shown in Panel B of Figure 3. Since the increased drought risk decreases production from the HW plant, there is no incentive for this plant to invest more. The differential investment by technology type in response to changing drought leads to the fourth hypothesis:

Hypothesis 4: *There will be relatively more investment in LW plants in areas with worse expected drought conditions.*

Lastly, notice that the market clearing price with the investment response by the LW plant is lower, offsetting some of the price shock relative to the non-drought scenario. By expanding the capacity available to absorb the shift in generation away from the drought

Figure 3: Investment Response of Stylized Market to Drought Shocks

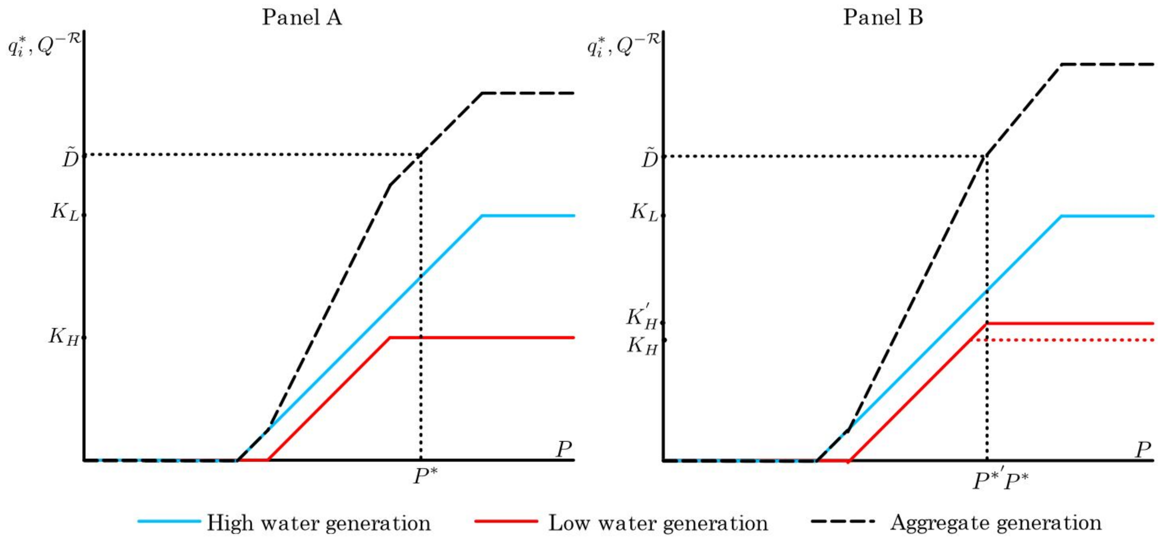


Figure shows stylized example of drought shock impact on capacity investment and wholesale prices.

affected plant, endogenous investment mitigates the impact of the drought shock in the spot market.

Hypothesis 5: *Investment in response to changing long-run drought conditions will mitigate some of the spot market effect of drought.*

4 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, wholesale spot market data, and drought conditions. These are detailed further in the subsections below. Supplemental data sources are highlighted in Appendix Section A.

4.1 Plant Characteristics

To identify power plant locations and characteristics, I aggregate generator level data 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 prime mover, 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.[6]

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. It is relevant to note that in the data plants can have multiple types of cooling systems (eg. switching over time or being dual equipped). Of the 1,098 thermal plants in the US for which I observe cooling information, 11% are observed with more than one type of operating cooling system. Since the choice of which system to operate is potentially endogenous and difficult to observe in the data[7], I drop the plants with multiple cooling technologies from my sample. Similarly, since the cooling data is available only since 2009, I assume that plants had the same technologies pre-2009 as they do post-2009.

I classify plants with once through cooled systems as "high water use", recirculating systems as "low water use", and dry cooled systems as "dry". Combustion generators do not require a cooling system, so I classify all combustion plants with no cooling data as "dry". Similarly, if a plant's main prime mover is wind or PV it does not have a cooling system and is categorized as "non-thermal". 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 are significantly larger 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.

[6] 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.

[7] Plants house multiple generators which are connected to potentially multiple boilers, which in turn are connected to potentially multiple cooling systems. Because of this structure, identifying the "main" cooling system for the plant and even a generator can be difficult and highly dependent on the researchers specification.

Table 1: Power Plant Characteristics

	Non-thermal	High Water	Low Water	Dry
Panel A: US Aggregate Statistics				
Number of plants	7,200	327	554	3,059
	(0.00)	(0.00)	(0.00)	(0.00)
Percent of total capacity	9	25	44	22
	(0.30)	(0.34)	(0.11)	(0.05)
Percent of total generation	7	27	60	6
	(1.39)	(1.27)	(1.09)	(0.65)
Panel B: US Plant Statistics				
Operating year	2016.12	1960.42	1987.53	1991.48
	(5.87)	(12.41)	(20.31)	(22.66)
Age at retirement	19.67	58.09	43.67	30.14
	(10.59)	(11.66)	(14.90)	(20.64)
Mean capacity (MW)	13.16	806.28	850.89	78.71
	(48.86)	(820.79)	(791.46)	(206.65)
Mean generation (GWh)	7.98	256.59	327.02	7.86
	(16.18)	(382.63)	(359.68)	(37.70)
Panel C: ERCOT Aggregate Statistics				
Number of plants	380	27	77	259
	(0.00)	(0.00)	(0.00)	(0.00)
Percent of total capacity	17	17	58	8
	(0.86)	(0.59)	(0.52)	(0.19)
Percent of total generation	16	5	72	7
	(3.57)	(1.21)	(3.50)	(0.83)
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)	43.47	591.16	717.84	27.83
	(85.56)	(572.77)	(428.72)	(129.31)
Mean generation (GWh)	28.27	68.42	255.60	21.01
	(25.39)	(91.63)	(185.37)	(65.01)
Non-zero generation indicator	0.96	0.67	0.90	0.70
	(0.20)	(0.49)	(0.30)	(0.46)

Table presents descriptive statistics for power plants in the US that were operational at any point since 2000 and additional statistics for the power plants located in ERCOT.

4.2 Market Data

To measure key market variables, I combine EIA-923 data on monthly plant level net generation with ERCOT market data on DAM prices and load. For demand, I aggregate hourly market level measures to a monthly measure of load (total quantity demanded). For prices, data is available in 15 minute intervals since 2010 for both the market average and hub level. I average the 15 minute prices to construct the average market level and hub specific price, as well as hub level average peak and non-peak period prices, for each month. I drop February 2021 from my analyses due to an extreme winter storm which resulted in outlier market data.

4.3 Drought Data

I measure water availability with monthly total precipitation and drought, both collected from the NOAA Monthly U.S. Climate Divisional Database. While there are many alternative measures of drought, I use 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 numbers reflecting more severe drought and 0 indicating normal conditions.[8] 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. The normalization process means that drought is interpreted as a deviation away from the climate division's average water availability. This means that while some areas consistently have more water than others, on average all areas should have a zero PHDI value. 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 4 presents a visual example of this variation.

[8] I scale the raw PHDI data by -1 to make worse drought a more positive number for ease of interpretation.

Figure 4: Map of Average Drought

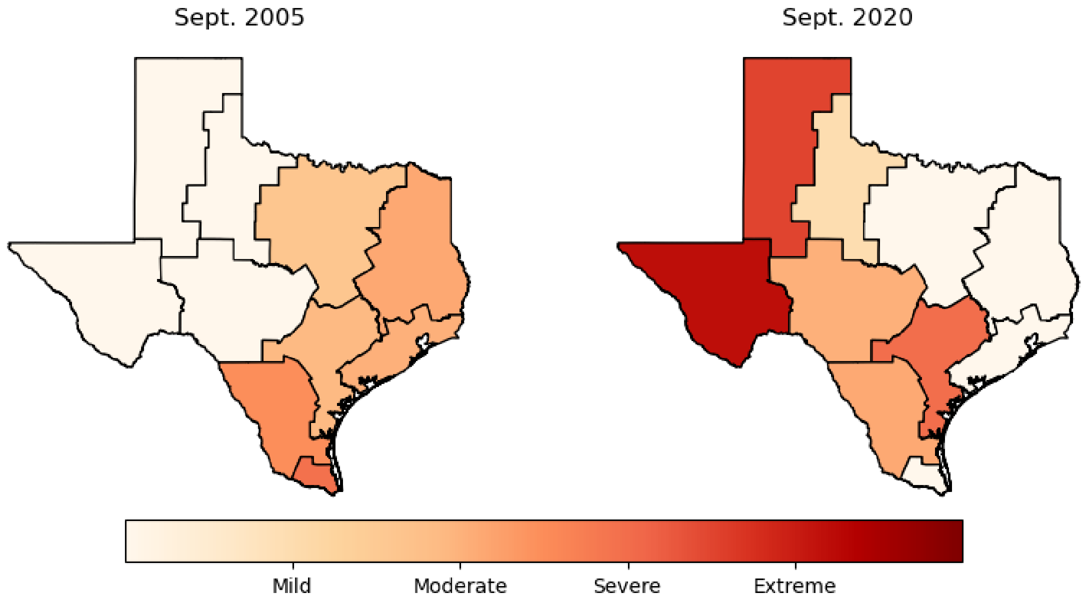


Figure maps PHDI index values for climate divisions in Texas in September of 2005 and 2020. Hash marks denote the beginning of drought severity category.

5 Empirical Evidence on Spot Market Outcomes

This section uses data on plant production, prices, and drought to answer the first research question (how drought affects production) by empirically validating the first three hypotheses outlined in the simplified framework in Section 3. I first show that in line with the framework, drought shocks shift generation in the spot market away from high water use plants and towards dry cooled plants (Hypothesis 1). Drought also leads to a higher market clearing price (Hypothesis 2), with a magnified effect during non-peak hours. I argue that the heterogeneity for prices is due to the relative differences in marginal costs between the price setting plants and the substitute plants across different levels of demand (Hypothesis 3). In total, the results from this section empirically document that drought impacts the spot market equilibrium, shifting generation towards less water intensive generation and increasing market clearing prices.

5.1 Correlation Between Drought and Spot Market Generation

I use fixed effects regressions at the plant level to show that worse local drought reduces generation from high water use plants, while worse average drought outside of a climate division increases generation from dry plants. The relationship with local drought aligns with Hypothesis 1, supporting the idea that drought is costly for directly affected high water use plants. The relationship between dry generation and average drought conditions instead emphasizes the importance of market dynamics when considering the full impact of drought.

5.1.1 Methodology

I regress measures of production on local and non-local drought conditions, as well as a set of covariates, to estimate the impact of drought on generation for each of the four technology types. For the sample of operating plants in ERCOT, I estimate the following specification for plant i in period t:

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

I estimate Equation 1 separately for each of the four technology types j, denoted by the coefficient superscripts, to allow for greater flexibility in the relationship between the covariates and outcomes of interest. The vector of covariates $X_{i,t}$ includes a linear year trend, quadratic in local temperature, total generation in ERCOT from nuclear sources, and the average hub price for the plant, instrumented for by total ERCOT load. Instrumenting for price with load is common in the literature, and is valid if quantity demanded is only related to production through prices, which is reasonable due to the highly inelastic nature of short run electricity demand. A more thorough discussion on this is presented later in Section 7.1.2. I also include month-of-year and climate division fixed effects to account for seasonality in production and unobserved regional characteristics such as operating expenses or non-market production needs.[9] Standard errors are clustered at the climate division level.

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

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

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).[10] The unconditional probability that a 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.

The impact of local and non-local drought conditions on production is captured by the set of coefficients denoted by $\boldsymbol{\alpha}^j$ and $\boldsymbol{\beta}^j$ in Equation 1. Local drought is measured using the PHDI value of month t for the climate division l where the plant is located. The non-local drought in contrast is the average of the PHDI values in month t across the nine other climate divisions in Texas. I use the following standard cutoff PHDI values to categorize both drought measures into five bins: no drought [-4, 1), mild [1,2), moderate [2,3), severe [3,4), and extreme [4,10).[11] I use categorical measures of drought to allow for non-linearities in the production response.

Interpreting $\boldsymbol{\alpha}^j$ and $\boldsymbol{\beta}^j$ as the causal effect of drought conditions on plant production requires the assumption that drought is conditionally exogenous. Given the stochastic nature of drought shocks this assumption seems generally reasonable, though there are some possible threats to identification. First, drought is positively related to higher temperatures (NOAA, n.d.), which in turn reduce thermal generation efficiency. The quadratic control for temperature in Equation 1 aims to limit the potential bias from this relationship. Second, drought may also have demand side impacts, for example by increasing electricity use for

[10] 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.

[11] 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).

irrigation. These correlated demand shifters would impact the quantity generated through increased wholesale prices. To account for this potential source of confounding, I control for average wholesale energy prices. Lastly, 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 estimate would jointly capture the direct effect and fuel cost effect, and is not readily resolved by simply controlling for natural gas fuel prices. 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.[12] It is worth noting that as natural gas plants are a significant share of all three thermal technology groups, all three groups are likely to experience similar impacts from the drought-fuel cost channel but should experience heterogeneous impacts from the drought-cooling channel. Therefore, in the case of severe bias, cross-technology comparisons should still be informative about differential impacts of drought on production. Further discussion on natural gas prices and drought is included in Appendix Section **??**.

5.1.2 Results

Share of Capacity Used Local drought conditions appear to affect high water use plants, significantly reducing the average share of capacity used for generation. As shown on the left side of Figure 5, the marginal effect estimates on local drought are steadily decreasing with drought severity for high water use plants. 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. Dry cooled plants also show an unexpected reduction in generation with local drought severity. One concern with this result is that dry cooled plants are more likely to

[12] 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.).

be privately owned for primary use with manufacturing or other purposes. It is possible that the private energy demand is impacted by drought, leading to the observed reduction in generation rather than a direct production impact. There appears to be some evidence of this argument, shown in Figure A7, since the strong decline in generation is not observed for utility scale plants. For the other technology types, the marginal effect estimates are fairly stable across drought conditions, reflecting a limited drought effect. These findings support the first part of Hypothesis 1 from the simplified framework.

Non-local average drought conditions instead appear to affect only dry plants, slightly increasing the average share of capacity used, conditional on running. As shown on the right side of Figure 5, the marginal effect estimates on non-local drought are generally increasing with drought severity 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 share of capacity used by dry plants by 2.5 percentage points relative to average non-drought conditions. The average share of capacity used by dry plants when producing is 38%, making the 2.5 percentage point increase a 7% increase. The marginal effect estimates for the other technologies are again fairly stable across drought severity. This finding supports the second part of Hypothesis 1 from the simplified framework.

The different changes in generation along the intensive margin for local and non-local drought underscore the importance of market dynamics. To see how, first consider the results in Figure 5 which show that production by high water use plants in location L declines with a local drought, but production from others in L doesn't change on average. Ignoring market dynamics, this would imply that total generation in the market declines. However, Figure 5 also shows that plants in the rest of the market respond to a drought in L, with dry cooled plants increasing production. If the drought shock affects only area L so that the market wide average drought is still low, then there is limited change in production by plants in the rest of the market. This makes sense: since only a few plants are impacted, there is a relatively small aggregate reduction in generation and the remaining plants in the rest of the market only need to increase production slightly to offset the loss. If the drought shock is instead widespread, many plants are impacted so there is a relatively large aggregate reduction in generation and the remaining plants in the market need to significantly increase

Figure 5: Drought Effect on Share of Capacity Used for Generation

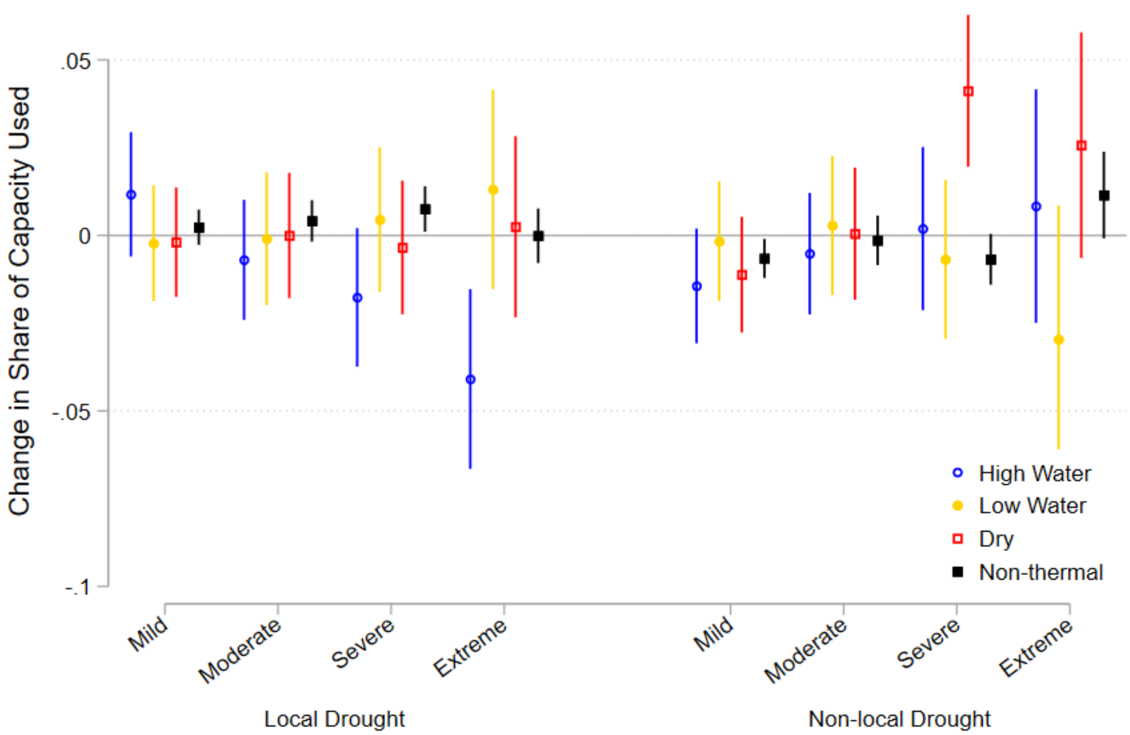


Figure plots marginal effect estimates for the impact of local and non-local drought on the share of capacity used for generation. The analysis is run separately for each of the four technology groups shown in the legend. Non-drought conditions are the omitted category for both local and non-local drought.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

production to offset the larger loss. This appears in Figure 5 as the production by dry cooled plants increasing with average drought in the market.

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. 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).

Probability of Running It appears that the increase in generation from dry plants is in part driven by plants coming online, while high water use plants cut back rather than go offline completely. These dynamics are captured in Figure 6, which shows the estimated marginal effect for local and non-local drought on the probability a plant is running. On the left hand side, it appears that there is no change in the probability a plant is running across any of the four types, including high water use. To align with the previously observed reduction in output during local drought, it must be that high water use plants reduce their average production but still produce. The right hand side of the figure shows positive and statistically significant marginal effects on non-local drought for dry plants but not for the other types of plants. The positive marginal effects on dry plants then means that at least part of the previously observed increase in generation is due to plants that were formerly not producing coming online. It's 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).

The change along the extensive margin for dry plants is interesting because it provides insight into the cost of substitution. As outlined in Section 2, with merit order production the lower cost plants are operated before the higher cost plants. This implies then that, in a given period, the plants that are observed operating must be cheaper, and likely more efficient,

Figure 6: Drought Effect on Probability Plant is Running

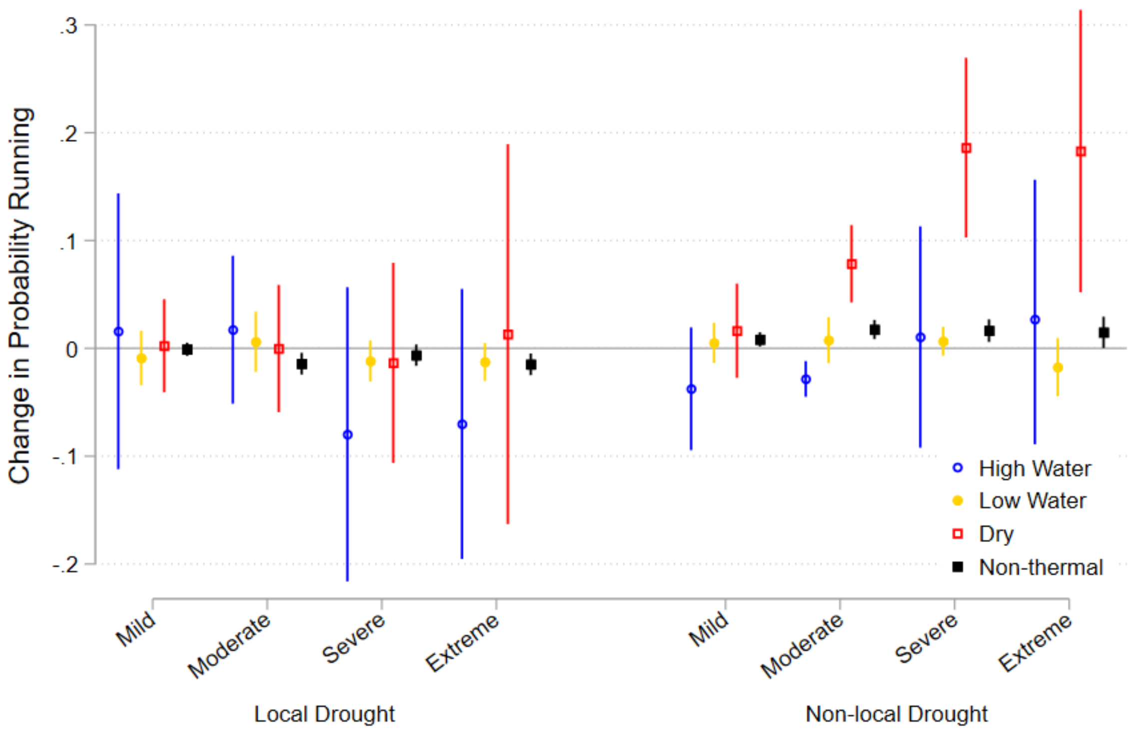


Figure plots estimated marginal effects for the impact of local and non-local drought on the probability that a plant is running. The analysis is run seperately for each of the four technology groups shown in the legend. Non-drought conditions are the omitted category for both local and non-local drought. Standard errors are clustered at the plant level. 95% confidence intervals are denoted by the vertical bars.

than those plants not operating. Following this logic, the dry plants coming online in Figure 6 are likely more expensive and less efficient than the high water use plants they are replacing. Additionally, since these dry plants are also now the marginal price setting plant, we would expect the wholesale price to increase. Overall, 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 (like natural gas).

5.2 Correlation Between Drought and Spot Market Prices

I use fixed effects regressions at the plant level to show that worse average drought in the market significantly increases wholesale electricity prices, with a larger impact on non-peak prices than peak prices. The increase in average wholesale prices aligns with Hypothesis 2, supporting the notion that drought induced changes in generation lead to more costly production. The difference in effect magnitude across peak and non-peak prices aligns with Hypothesis 3, underscoring that the plants which substitute for the lost energy from high water use plants are critical to determining the total effect of drought.

5.2.1 Methodology

I follow an almost identical regression specification as that shown in Equation 1 to examine the relationship between drought conditions and hub level wholesale electricity prices. For the sample of operating plants in ERCOT, I estimate the linear regression

$$ln(P_{i,t}) = \sum_{z \in Z} \alpha_z \text{Drought}_{l,t} + \sum_{z \in Z} \beta_z \overline{\text{Drought}}_{-l,t} + \Gamma X_{i,t} + \phi_i + \phi_{m(t)} + \varepsilon_{i,t} \tag{2}$$

Unlike previously, I estimate Equation 2 only once, combining all technology types. The controls denoted by $X_{i,t}$ include a linear year trend, a quadratic in local temperature, total generation in ERCOT from nuclear sources, and the natural log of total ERCOT load. I also include month-of-year and plant fixed effects. Standard errors are clustered at the plant and month-of-sample level. I cluster at month-of-sample level to account for cross-sectional correlation in the error term arising from assigning hub level prices to plants.

I pull DAM hub prices (described in Section 2.2) to use as my outcome variables, focusing on the average price, the average peak price, and the average non-peak price. I construct the average price as the average of the 15 minute hub price over all of month t for plant i. The average peak and non-peak prices are instead constructed respectively as the average of the 15 minute hub price over all of the peak (1pm to 7pm) and non-peak (7pm to 1pm) hours during month t. 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. Note also that this means the coefficient on the natural log of total load can be interpreted as the inverse price elasticity of demand. The estimates of these coefficients are shown in Table **??** of the appendix.

Two key conditions must hold to have the estimates of this analysis reflect how prices respond to the drought driven production changes observed previously. First, drought cannot also be shifting the demand curve. To account for the possibility that this relationship exists, I directly control for temperature and quantity demanded. Second, there cannot be additional drought related supply shifters beyond the change in production. For example, this could include changes in nuclear generation or input prices. While I control for monthly nuclear generation, I am unable to control directly for other potential supply side confounders. Similar to before, natural gas prices are likely to be the main confounding supply shifter. Including a month-of-sample fixed effect would effectively address this concern, however the identification of the parameters of interest for non-local drought would be relatively weak since it would be relying on limited cross-sectional variation in the average drought conditions outside of each climate division. If drought increases natural gas prices, then all else equal this would increase wholesale prices leading to an upward bias.

5.2.2 Results

There is a limited relationship between local drought conditions and wholesale energy prices. In general, the left of Figure 7 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, and seems reasonable given the fact that prices are an equilibrium outcome of the market at large. 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 7 shows a 36% increase in average wholesale prices received 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 \$10.22 increase relative to the median price of \$28.36. This larger effect, relative to the negligible local effect, is likely driven by the increase in the market share of plants that are adversely affected by drought. 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. As discussed previously, the dry cooled plants that come online to replace the lost generation are likely less efficient, pushing prices higher as more substitute production is needed. This finding aligns with Hypothesis 2 from Section 3, that drought shocks will (weakly) increase prices.

Non-peak prices consistently respond to drought more than peak prices, providing evidence that the price effect is driven by the merit order of the substitute plant relative to the price setting plant (Hypothesis 3). To explore this dynamic, first consider non-peak hours when demand is low. Due to merit order ranking, lower marginal cost plants (non-thermals, high water use, low water use) should be operated first, while higher cost dry cooled plants should function as peaker plants. This means that in periods of low demand without drought, the price setting plant is likely a low marginal cost plant. However, by the previous analyses, introducing a drought shock increases generation by dry cooled plants. This would then mean that the new price setting plant is a high cost dry cooled plant, leading to large increase in price relative to the non-drought, low cost price setting 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 7 shows, highlighting the idea that the price effect magnitude is largely determined by the available substitute plants relative

Figure 7: Drought Effect on Wholesale Prices

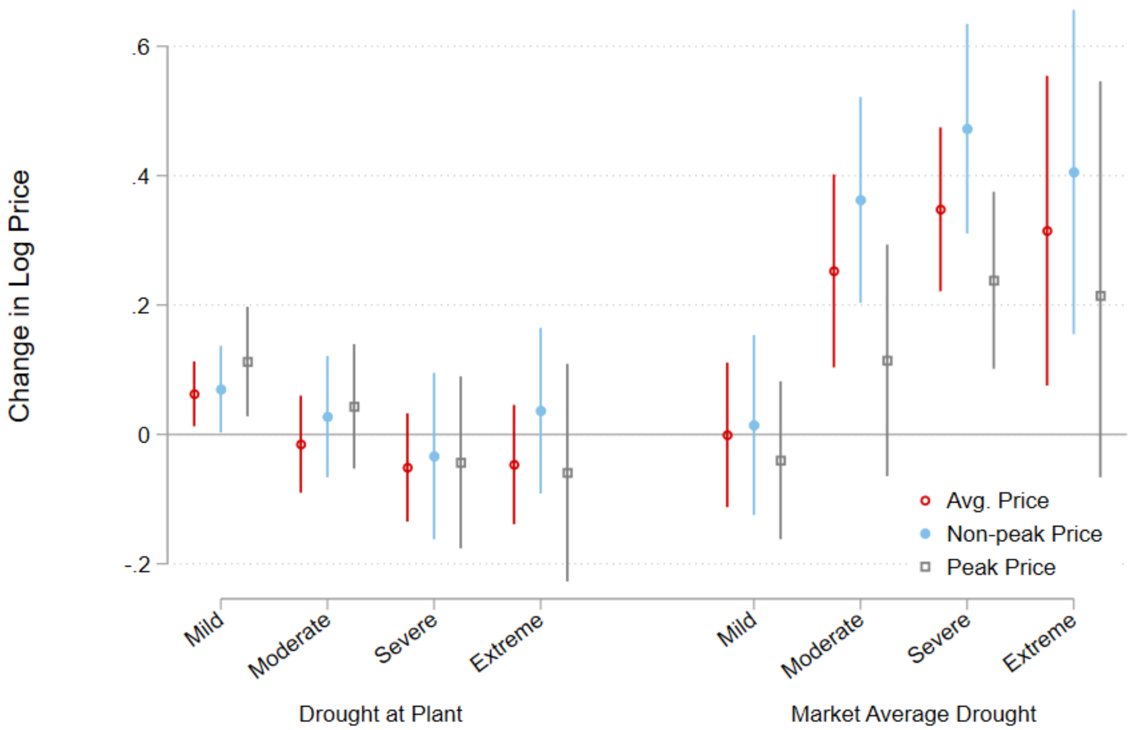


Figure plots marginal effect estimates for the impact of local and non-local drought on wholesale prices. The analysis is run separately for each of the three prices shown in the legend. Non-drought conditions are the omitted category for both local and non-local drought. Standard errors are clustered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

to the 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. Additionally, McDermott and Nilsen (2014) estimate a price elasticity of supply between 0.1 and 0.2 in Germany, while Bushnell, Mansur, and Saravia (2008) estimate a price elasticity of supply for competitive firms in US markets between 0.02 and 0.7, depending on the market. My estimate for the average price elasticity of aggregate supply of 0.2 (inverse of coefficient on log of ERCOT load, shown in Appendix Table **??**) aligns well with these other estimates. The low elasticity shows that total generation in the DAM is highly inelastic with respect to DAM prices, which seems reasonable given the need to consistently fulfill inelastic demand, the limited scope of price response for non-thermals, and (important for this analysis) binding capacity constraints limiting production.

5.3 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.

Impact on Capacity Constrained I additionally examine the impact of drought on the likelihood that power plants are capacity constrained, using the same framework at Equation 1. While it is rare that plants operate at capacity, it is an important production aspect to understand how stressed the electric grid is. 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.

Instead of measuring drought with the PHDI index, 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 toa one standard deviation reduction in non-local precipitation, but otherwise generally negligable and imprecise impacts for other thermal plants.[13] Non-thermal generators show increases in production with reductions in precipitation both locally and non-locally. Table A2 shows that the observed generation changes are not associated with any change in prices. Measuring precipitation in both levels and deviations shows negligable impact on prices. The limited response when measuring drought with precipitation is explainable by the fact that precipitation is a relatively short run measure, and one particularly dry month is unlikely to significantly affect reservoir levels and stream flows. In contrast, the PHDI which is in part based on precipitation, aggregates the short run precipitation shocks into longer aggregate trends that are more meaningful for plant operations.

Turning back to the PHDI measure, I re-estimate my main results measuring drought using different functional forms of the PHDI. I start by examining drought duration (measured as continuous months in at least moderate drought), since longer duration droughts may have worse effects as buffer water supplies are depleated. The results for production and prices are shown in Tables A3, A4, and A5. I find that a one month increase in either local or non-local drought duration has negligable impacts on production quantites. However, Table A5 shows small but statistically significant increases in prices of around 1%. The 75th percentile of both drought duration measures in the data is about 13 months, leading to an economically meaningful price increase for long droughts. I next focus on prices as a function of the number of climate divisions that are in at least severe drought. The results from this are shown in Figure A5, and show that prices increase when a majority of climate

[13] 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.

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 A6. *From these results, the key takeaway is that it appears that what matters for prices is 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 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 A7 I repeat my analyses excluding non-utility owned power plants which are likely producing energy for reasons other than selling to the grid, and may push results towards the null. The figures shows similar results as the main analysis for all but dry cooled plants. The increase in production by these plants is larger than the main result, likely reflecting downward pressure on the coefficient from non-sale purpose generation. Similarly, in Figure A8 I repeat the main analyses excluding combined heat and power plants which again produce electricity for non-market (heating) reasons. The results are again similar for all technologies but dry cooled plants, with non-local drought increasing their production even more. Additionally, local drought also now reduces the share of capacity used by dry cooled plants.

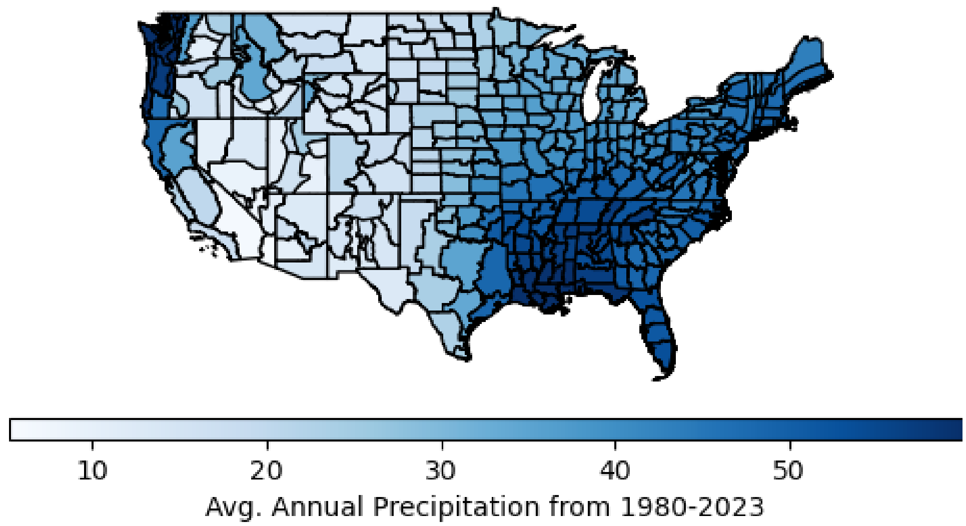
I next vary the range of time used in the analyses. In Figure A9 and Figure A10, I repeat the main analyses excluding observations from June through September. Summer is peak electricity demand in Texas, and high demand can lead to transmission congestion which would limit the ability of plants to trade electricity across space. Excluding summer months acts as a crude way of eliminating impacts on prices and production from this congestion. I find similar generation impacts for all technologies, though the changes for dry cooled generation are attenuated. Similarly for prices, the results are generally similar to the main analysis though attenuated. The reduced impact likely reflects that during low demand in winter, there are more plants available to substitute for the reduced high water use generation that are earlier in the merit order (cheaper). Lastly, I repeat the analyses on production seperating the data into pre-2010 and post-2010 to account for the fact that the rapid rise of cheap natural gas starting in 2010 (via fracking) shifted the generation mix of technologies, and as such may have changed the estimated effect of drought. A caveat with this analysis though is that price data in unavailable pre-2010, so I directly control for total load instead of instrumenting for price. The results for the share of capacity used are shown in Table A6. The results before 2010 roughly align with the results from the main analysis post-2010. However, these results should be interpreted with caution, since excluding the control for price leads to very different coefficient estimates for the post-2010 period. Without earlier price data it is impossible to better untangle heterogeneity in effect resulting from the fracking boom. *In total, changing the sample selection process appears to have a limited impact on the main takeaways of the analysis.*

6 Empirical Evidence on Investment Decisions

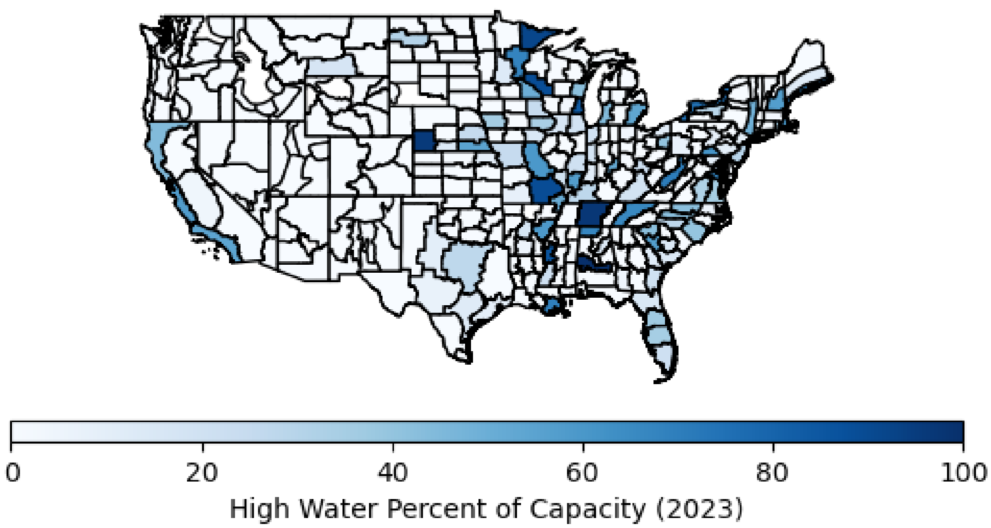
This section aims to understand the extent that high water use plants are located in relatively more water abundant areas, as predicted by Hypothesis 4 of the conceptual framework. Using average annual precipitation as a proxy for water availability, Figure 8 shows that the expected relationship holds in a simple spatial comparison, with the eastern half of the US being both generally wetter than the western half (8a) and having a larger share of capacity that is high water use (8b). However, this cross-sectional framework could be capturing many other factors, such as the eastern half of the US being more densely populated or being less productive for renewable technologies.

There are many challenges to estimating the causal effect of drought risk on generation investment in a reduced form structure. Under a cross-sectional framework, issues may arise through confounding factors on both the supply and demand side. For example, water availability is likely correlated with unobserved features that impact electricity supply, such as proximity to fuel and transmission infrastructure, as well as determinants of long run electricity demand, for example energy use for irrigation. Using longitudinal variation in drought conditions within a location helps mitigate some sources of confounding, but introduces new issues. Primarily, the fact that both average water availability and the generation mix can change very slowly providing little detectable variation.

Figure 8: Maps of Water Availability and Generation Mix



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



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

As a second best, I use 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 two steps of the investment process to define the outcome variables of interest: the probability that a planned generation capacity investment is canceled and the probability that a constructed plant is technology type j. For both outcomes I use the average drought conditions in the years preceding the event (cancellation or construction) to measure drought risk. By using plant level data I am able to exploit more of the temporal variation in drought conditions by linking plants in the same climate division to different drought conditions based on the different years of construction. This helps with identification, since it allows me to use climate division fixed effects to control for unobserved, time invariant environmental characteristics. 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 **??** 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.

6.1 Cancellation of Planned Capacity Investment

I first consider the probability that a planned investment is canceled as a function of drought and the type of technology the capacity would have used. The capacity investment can reflect both a whole new power plant or capacity growth in an existing power plant. The data on planned generators is available from 2015 through 2023 and contains the generator's planned operation date, year the generator was canceled if applicable, and fuel and prime mover. Without knowing the associated cooling system, I am only able to categorize observations as thermal combustion, thermal non-combustion (i.e. steam or combined cycle prime mover), or non-thermal. For each generator i that appears in the set of planned capacity investments, I create an indicator for if the generator is canceled at any point before 2023. I then regress this binary outcome using a probit transformation of the model

$$\begin{aligned}\mathbb{1}(\text{Canceled}_i) = \alpha_1 \overline{\text{PHDI}_{2000-2023}} + \alpha_2 \mathbb{1}(\text{Non-Thermal}_i) + \alpha_3 \overline{\text{PHDI}_{2000-2023}} \times \mathbb{1}(\text{Non-Thermal}_i) \\ + \alpha_4 \mathbb{1}(\text{Combustion}_i) + \alpha_5 \overline{\text{PHDI}_{2000-2023}} \times \mathbb{1}(\text{Combustion}_i) \\ + \Gamma X_i + \varepsilon_i \end{aligned} \tag{3}$$

The marginal effects estimated from the coefficients of interest α_1, α_3, and α_5 estimate the change in probability a generator is canceled due to a one index unit increase in local average drought between 2000 and 2023. The omitted group is thermal, non-combustion generators which roughly aligns with the union of high water use and low water use plants. Combustion thermal generators are almost exclusively dry cooled, so that α_5 is interpreted as approximately reflecting the difference in cancellation probability of dry cooled capacity relative to the other thermal capacity investments. The regression includes linear controls for the year the generator is planned to begin operation, county of plant level population density and growth, and a categorical variable for plant state, all denoted by X_i. Each observation is weighted by capacity, winsorized at the 90th percentile of the technology specific distribution. Standard errors are clustered at the climate division level.

The results of this analysis are shown in Table 2. For the subset of planned non-combustion thermal generators, one standard deviation worse recent drought conditions is associated with an increased probability of being canceled by 2023 of 3.8 percentage points, or 15% over the average probability, though the point estimate is statistically insignificant. In contrast, one standard deviation worse recent drought reduces the cancellation rate of combustion and non-thermal investment, with non-thermals showing a statistically significant 8 percentage point decline (28% over the base rate). Overall, the results from this analysis suggest that worse historic drought conditions leads to more investment in non-thermal sources, with potentially small reductions in more water intensive generation capacity.

6.2 Construction of High Water Use Plants

I next turn to the constructed thermal plants, and look at the probability that a plant uses high water use technologies as opposed to low water use or dry. Unlike the previous analysis, this analysis is able to benefit from significant variation in the time of construction. For

Table 2: 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.

each plant, I link the plant to the 10 year average drought index before the plant was built in period t. The underlying assumption with this specification is that the average drought conditions preceding plant construction fully reflect firms' expectations over future drought conditions. To test the validity of this, I also include the 10 year average drought after the plant was built. If firms' expectations over future drought are fully captured with the lagged drought, then the future drought measure should have a zero coefficient. If instead firms have correct information over subsequent future drought not captured by the lagged drought measure, the lead term should have a non-zero coefficient.

The formal regression specification used is a probit transformation of the equation

$$\mathbb{1}(\text{High Water Use}_i) = \alpha_1 \overline{\text{PHDI}_{t,t-10}} + \alpha_2 \overline{\text{PHDI}_{t,t+10}} + \phi_l + \phi_t + \varepsilon_i \tag{4}$$

I include climate division and decade built fixed effects, clustering standard errors at the climate division level. I again weight each plant by its capacity, winsorized at the 90th percentile of the technology specific distribution.

The results of this analysis are shown in Table 3. 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 5 percentage points, over a base of 31 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 13%. Across the board, controlling for drought after construction returns small and statistically imprecise coefficients. This provides suggestive evidence that plant developers respond to observed drought pre-construction, but conditional on that information the subsequent drought shocks are unpredictable. The takeaway supported by this analysis is that firms consider recent drought conditions when deciding what type of plant to build, with drier conditions correlated with an increase in low water use and, in particular, dry cooled technologies.

6.3 Additional Analyses

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

Table 3: Probability of Technology Choice for Constructed Plants

	(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 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 for each thermal technology. The sample average share capacity for each technology is shown at bottom. Standard errors are shown in parentheses and clustered at the climate division level.

Conditional correlation with precipitation I quantify the relationship shown in Figure 8 with OLS regression in Table A7. 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.*

Mothballing and retirement As an alternative to investment, I also examine disinvestment as a function of drought, defining disinvestment as either mothballing or retiring existing plants.[14] Similar to the main analyses, I look at the probability of mothballing or retirement as a function of the drought conditions leading up to the event. For mothballing, Table A8 suggests that high water use plants are more likely to be mothballed after worse drought conditions, with the probability increasing with drought severity in the last

[14] I define mothballing as a plant not being formally retired but not operating for more than one year.

year. The other thermal technologies do not show a similar correlation with the last year's drought. For retirement, Table A9 suggests that high water use plants are more likely to be retired after worse drought conditions and the other technologies are less likely to retire, though all of the point estimates are imprecisely estimated. *The analyses provide suggestive, though statistically imprecise, evidence that drought also drives disinvestment in high water use technologies.*

Total investment Drought may also impact whether there is any investment in a location at all. To examine this, Table A10 uses a climate division by decade panel to estimate the change in total capacity investment as a function of standardized previous drought conditions. The results show minimal differences in level changes, with a one standard deviation worse average drought last decade being associated with a 1.3% (6,364 MW) difference in total installed capacity. The lack of difference is also reflected in the log transformation of the outcome variable, though the sign of the coefficient is flipped. The lack of difference in total capacity aligns with the results in the last two columns, that there is little difference in new investment across locations as a function of drought. *The results suggest that the total amount of capacity constructed is largely determined by forces exclusive of drought.*

Separating coal and natural gas A potential concern is that structural change in electricity markets due to the proliferation of cheap natural gas is driving the observed correlations with drought. To examine this, I repeat the exercises for the outcomes of technology type of new plants, mothballing, and retirement separately for coal and natural gas plants. For technology choices of new plants, I find suggestive results in Table A11 affirming the main findings that worse drought reduces investment in high water use technologies for natural gas, and does not decrease investment in low water use or dry technologies. Unlike the main analysis though, the coefficients on drought after investment are larger and sometimes statistically significant, though the coefficients agree in direction with drought adversely impacting high water use technologies. For mothballing existing plants, Table A12 shows a suggestive increase in mothballing for both coal and natural gas high water use plants, while again there is little change in the other technologies. For retirement, Table A13 shows statistically significant decreases in retirement hazard for high water use natural gas plants, and small increases for both high water and low water use coal plants. Due to thin sample sizes, this analysis does not stratify on climate division which is likely driving some of the differences in coefficients compared to Table A9. *Overall, it does not appear that the main results on the correlation between drought and investment are driven disproportionately by growth in natural gas and reductions in coal, but instead the results across both fuels are generally consistent with the main findings.*

New investment by technology type Alternatively to measuring investment at the plant level, I examine new investment at the climate division by decade level. I aggregate time to the decade level since investment is fairly infrequent and there are many years with zero investment. I measure investment by technology as the share of new capacity constructed in a location that uses the respective technology. The results, shown in Table A14 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, there is suggestive evidence that the plant level results hold, though the statistical precision is very weak and the coefficient magnitudes are relatively attenuated.*

7 Model Framework

This section presents the empirical model of investment in capacity and electricity generation in ERCOT. The main goal of the model is provide a framework that can be used to simulate the market under alternative drought scenarios. To accomplish this, the model incorporates drought as a determinant of production costs in the spot market. This buys me two things. First and foremost, it allows me to make plant investment endogenous to drought conditions, providing insight into how the equilibrium generation mix may respond to climatic changes. Second, it provides a more rigorous framework to understand the spot market response to drought, by more thoroughly accounting for market dynamics than reduced form analyses.

The model is populated with heterogeneous firms, where I treat a firm as a unique plant, categorized by two key characteristics. First, each plant is one of four mutually exclusive technology types: non-thermal (NT), high water use (HW), low water use (LW), and dry (NW). The assigned technology type, denoted j, determines a plant's investment and production costs as well as its water needs - and therefore exposure to drought shock costs. Incorporating heterogeneity along technology type is important for examining shifts in the generation mix. Second, each plant is assigned to one of several locations $l \in L$ to build in, which determines the environmental shocks that the plant is exposed to. Spatial heterogeneity is important to both reflect cross-sectional variation in drought conditions and to capture spatial sorting of different technologies.

The decision process of each plant in the model is outlined by the following structure. First, in an initial investment period 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 the maximize expected discounted profit flows and the market prices which ensure the spot markets clear.

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 particularly 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.

The remainder of the section is divided into two parts. The first section outlines the plants' optimal capacity choices for the investment decision. The second part details the spot market structure and the resulting optimal generation decisions.

7.1 Investment in Capacity

7.1.1 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

$$V(K_i) = \mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi^j(\eta_t, P_t, K_i)] - \delta_1^{j,l} K_i - \delta_2^j K_i^2 - \nu_i K_i \tag{5}$$

In period $t = 0$, the plant must pay the investment costs of building capacity, which the model assumes are a quadratic in capacity, reflected by δ_1^j and δ_2^j being non-zero. Plants also face 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, the equilibrium price P_t, and the realization of environmental and market state variables η_t. The model assumes that 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

$$K_i^* = \frac{\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, P_t, K_i^*)] - \delta_1^{j,l} - \nu_i}{2\delta_2^j} \tag{6}$$

The investment cost parameters, lifespan, and profit function are all technology type specific, as shown by the superscript j. Investment costs are technology specific since the different plant types face different regulatory restrictions and infrastructure needs, leading to heterogeneous investment costs. Notably, low water use plants generally require additional investment in cooling towers, resulting in a cost which the other plant types do not face. Similar technological differences drive variation in a plant's operational lifespan and production processes. I additionally allow for spatial variation in the linear investment cost parameter, denoted by the superscript l. Allowing heterogeneity in this parameter aims to capture regional differences such as access to transmission infrastructure and land use. Additionally, since any fixed operating costs in the spot market are not seperately identified from the linear investment costs, allowing spatial heterogeneity captures some variation in unobserved fixed operating costs.

7.1.2 State transitions

Uncertainty from a plant's perspective in $t = 0$ is over the realization of future state variables, production cost shocks, and the resultant market clearing wholesale prices. The state variables consist of the environmental variables of temperature $tmp_{l,t}$, drought $z_{l,t}$, and productivity of non-thermal generators $\omega_{l,t}$ in each location, and the market variables of generation from nuclear sources[15] Q_t^N and total load D_t. These variables are potentially correlated, both across space and time, and their distributions are known to the plants in period $t = 0$.

The model formalizes the relationships between state space variables through the

[15] Nuclear generation is also a water intensive thermal generation process. However the ability of these plants to change production is relatively limited, and investment in new nuclear plants is extremely rare. For my analysis I abstract from these plants and treat their production as exogenously determined.

following set of reduced form law of motion equations.

$$tmp_{l,t} = \beta_0^{tmp,l} + \beta_1^{tmp,l} year_t + \sum_{m=2}^{12} \beta_m^{tmp,l} month_t + v_t^{tmp} + u_{l,t}^{tmp,l} \tag{7}$$

$$\omega_{l,t} = \beta_0^{\omega,l} + \beta_1^{\omega,l} year_t + \sum_{m=2}^{12} \beta_m^{\omega,l} month_t + v_t^{\omega} + u_{l,t}^{\omega,l} \tag{8}$$

$$z_{l,t} = \beta_0^{z,l} + \beta_1^{z,l} z_{l,t-1} + \beta_2^{z,l} tmp_{l,t} + v_t^{z} + u_{l,t}^{z,l} \tag{9}$$

$$Q_t^N = \beta_0^{Q^N} + \beta_1^{Q^N} year_t + \sum_{m=2}^{12} \beta_m^{Q^N} month_t + \beta_{13}^{Q^N} Q_{t-1}^N + v_t^{Q^N} \tag{10}$$

$$\begin{aligned} D_t = &\beta_0^D + \beta_1^D year_t + \sum_{m=2}^{12} \beta_m^D month_t + \beta_{13}^D \frac{1}{L} \sum_l tmp_{l,t} + \beta_{14}^D \frac{1}{L} \sum_l tmp_{l,t}^2 \\ &+ \beta_{15}^D D_{t-1} + \beta_{16}^D P_{t-1} + v_t^D \end{aligned} \tag{11}$$

There are a few key features of the above specifications. First, the distributions of the environmental state variables in Equations 7-9 are location specific, seasonal (except z), subject to an idiosyncratic shock $u_{l,t}$, and correlated across space through a common shock v_t. Second, drought is both auto-correlated and correlated with local temperature, reflective of the natural hydrologic processes leading to drought. Third, while load is correlated with lagged prices, it is perfectly inelastic with respect to current prices P_t. This is a common assumption in this literature and stems from the structure of electricity markets. As discussed in Section 2.2, the majority of electricity is transacted through the bilateral forward market, meaning end consumers are primarily consuming, and responding to the price of, electricity that was transacted in this market rather than the DAM or RTM. The forward wholesale prices are agreed upon well in advance of the actual production of electricity, and are influenced by previous DAM and RTM market prices, but not current wholesale spot market prices. This structure means 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 in $t = 0$. 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 as the common knowledge function:

$$
\begin{aligned}
P_t = &\beta_0^P + \beta_1^P year_t + \sum_{m=2}^{12} \beta_m^P month_t + \beta_{13}^P \frac{1}{L} \sum_l tmp_{l,t} + \beta_{14}^P \frac{1}{L} \sum_l tmp_{l,t}^2 + \beta_{15}^P \frac{1}{L} \sum_l z_{l,t} \\
&+ \beta_{16}^P \frac{1}{L} \sum_l z_{l,t}^2 + \beta_{17}^P \frac{1}{L} \sum_l \omega_{l,t} + \beta_{18}^P Q_t^N + \beta_{19}^P D_t + \beta_{20}^P P_{t-1} + v_t^P
\end{aligned}
\tag{12}
$$

This structure assumes first that realizations of key state variables are sufficient to represent the underlying spot market process, and second that plants are agnostic about how their investment impacts 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.

7.2 Spot Market Generation

Within the subsequent generation periods, production is determined by the following process. First, the state variables evolve following the transition processes outlined by Equations 7-11, and cost shocks $\varepsilon_{i,t}$ are drawn from technology type specific, mean zero distributions. Second, non-thermal plants produce electricity as a function of their total capacity and the non-thermal productivity factors $\omega_{l,t}$. Third, thermal plants observe market prices and then produce electricity so that fourth, the market clears or all plants produce at capacity.

7.2.1 Non-thermal generation

Production by non-thermal plants is assumed to be price inelastic and determined by exogenous environmental conditions in the location of the plant, such as wind speed and cloud cover. The model ignores the details of how these environmental factors impact generation and instead 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 in a given period is given by

$$
q_{i,t}^{NT}(\eta_t, K_i) = \begin{cases} 0 & \text{if } \omega_{l,t} + \phi_i + \varepsilon_{i,t} < 0 \\ (\omega_{l,t} + \phi_i + \varepsilon_{i,t}) K_{i,t} & \text{if } \omega_{l,t} + \phi_i + \varepsilon_{i,t} \in [0, 1] \\ K_{i,t} & \text{if } \omega_{l,t} + \phi_i + \varepsilon_{i,t} > 1 \end{cases}
\tag{13}
$$

The $\omega_{l,t}$, which as Equation 8 shows is drawn from a time dependent distribution with correlation across space, reflects aggregate and seasonal changes in productivity (eg. wind turbines produce less in summer). The next term ϕ_i captures persistent plant specific productivity, reflecting that some plants are on average more productive (eg. a wind farm being in a windier location). The last term $\varepsilon_{i,t}$ captures highly localized, time varying shocks. Plants are constrained by their capacity, so they cannot produce more than K_i or less than 0.

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

$$\pi^{NT}(\eta_t, P_t, K_i) = P_t q_{i,t}^{NT}(\eta_t, K_i) \tag{14}$$

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.

7.2.2 Thermal generation

Production by thermal plants takes prices as given and is determined by selecting the generation quantity that maximizes current period profits. Under the assumption of a competitive market, this optimal quantity is where the plant's marginal cost equates the market price. Plants' production costs depend on the costs of direct inputs (eg. labor, fuel, and water) and indirect determinants of productivity (eg. air temperature and share of capacity used). Both input costs and determinants of productivity are likely to have significant variation across space and time. Additionally, how these factors translate into production costs is going to be heterogeneous by technology type. For example, water is an essential input for high water use and low water use generation, but not dry cooled generation.

I parameterize the spot market production cost functions for each technology type using the following specification,

$$c^j(q_{i,t}^j) = \lambda_1^j q_{i,t}^j + \lambda_2^j \frac{q_{i,t}^2}{2K_{i,t}} + q_{i,t}^j(\rho^j z_{l,t} + \gamma^j X_{i,t} + \phi_i + \varepsilon_{i,t}) \tag{15}$$

This specification of production costs is similar to others in the literature (Butters, Dorsey, and Gowrisankaran, 2021; Elliott, 2022). Costs are non-linear in $q_{i,t}^j$, and in particular dependent on the level of production relative to capacity. This reflects a mechanical feature of generators where their efficiency depends on the level of output and generally peaks at levels below capacity. I also include a set of covariates $X_{i,t}$, almost identical to those used in the reduced form analysis detailed by Equation 1, consisting of local temperature and its square, average drought elsewhere in the market, a linear year trend and season fixed effects. I also include permanent productivity differences through plant fixed effects, 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_1^j and λ_2^j 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 an increase 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 notation simplicity, I denote the local drought conditions as $z_{l,t}$, but in practice I treat local drought conditions as falling into one of three categories: No drought, moderate to severe, or extreme. Incorporating drought in this way allows for non-linearities in the relationship with production costs. Additionally, all parameters are technology specific, which is crucial with respect to drought conditions to capture the heterogeneous impact of drought shown in Section 5.1.

Under the cost function in Equation 15, profit maximization leads to the following optimal generation choice for thermal plants,

$$q_{i,t}^j(\eta_t, P_t, K_i) = \begin{cases} 0 & \text{if } P_t < \Lambda_{i,t} \\ \frac{P_t - \Lambda_{i,t}}{\lambda_2^j} K_i & \text{if } \Lambda_{i,t} < P_t < \Lambda_{i,t} + \lambda_2^j \\ K_i & \text{if } P_t > \Lambda_{i,t} + \lambda_2^j \end{cases} \tag{16}$$

$$\text{where } \Lambda_{i,t} = \lambda_1^j + \rho^j z_{l,t} + \gamma^j X_{i,t} + \phi_i + \varepsilon_{i,t}$$

Plants cannot produce negative amounts of electricity[16], so for sufficiently low prices, $P_t <$

[16]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.).

$\Lambda_{i,t}$, 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 $P_t > \Lambda_{i,t} + \lambda_2^j$ 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.

$$\pi^j(\eta_t, P_t, K_i) = \begin{cases} 0 & \text{if } P_t \leq \Lambda_{i,t} \\ K_i \frac{(P_t - \Lambda_{i,t})^2}{2\lambda_2^j} & \text{if } \Lambda_{i,t} < P_t < \Lambda_{i,t} + \lambda_2^j \\ K_i(P_t - \Lambda_{i,t} - \frac{\lambda_2^j}{2}) & \text{if } P_t > \Lambda_{i,t} + \lambda_2^j \end{cases} \tag{17}$$

7.2.3 Wholesale Prices

The equilibrium spot market price is determined by the intersection of the residual demand faced by thermal plants and the aggregated thermal supply curve. Residual demand faced by thermal plants equals the total demand, drawn as a state variable at the start of the period, less the total amount of nuclear generation and generation from non-thermal plants.

$$\tilde{D}_t = D_t - Q_t^N - \sum_{i \in NT} q_{i,t}^{NT}(\eta_t, K_i) \tag{18}$$

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 $Q^T(P_t)$ that is a linear piece-wise function over P_t with $2(|HW|+|LW|+|NW|)+1$ many segments. Inverting the aggregate supply curve at $\tilde{D}_t$ returns the market clearing price $P_t^* = Q^{T^{-1}}(\tilde{D}_t)$.

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 and nuclear generation are sufficient to entirely fill demand, so that no costly thermal generation is necessary. For constructing the counterfactual generation mixes, I assume that in the event of blackouts $P_t^* = \max_i(\Lambda_{i,t} + \lambda_2^j + 1000)$ and in the event of excess non-thermal generation $P_t^* = 0$.

8 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 then use these to construct estimates of expected marginal profit flows which I use to estimate the investment cost parameters.

8.1 Spot Market Production Costs

Solving for the firms' optimal generation each period requires knowing the parameters determining the marginal cost functions, which I estimate from the firms' first order conditions. I do not directly observe the marginal cost associated with different levels of production for each firm, and instead observe only 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. Under the assumption of perfect competition though, the firms' first order conditions dictate that optimal generation is where $P_t = c'^j({q^*}^j_{i,t})$. Solving for ${q^*}^j_{i,t}$ from this condition as in Equation 16, which is replicated and slightly rearranged below, then gives me a usable structure to estimate the cost function parameters with regression analysis.

$$\frac{{q^*}^j_{i,t}}{K_i} = \begin{cases} 0 & \text{if } P_t < \Lambda_{i,t} \\ \frac{P_t - \Lambda_{i,t}}{\lambda^j_2} & \text{if } \Lambda_{i,t} < P_t < \Lambda_{i,t} + \lambda^j_2 \\ 1 & \text{if } P_t > \Lambda_{i,t} + \lambda^j_2 \end{cases} \tag{19}$$

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

In absence of the capacity constraints, the firm's optimal $\frac{{q^*}^j_{i,t}}{K_i}$ from the first order condition would be equal to the second piece of Equation 19, $\frac{P_t - \Lambda_{i,t}}{\lambda^j_2}$. 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. To account for the censoring between 0 and 1, I estimate Equation 19 with a tobit regression model, estimated with maximum likelihood. Note that this specification is essentially identical to that used in the reduced form analyses of generation shown in Equation 1, with the main differences being that I define only two categories of drought and use the market average price instead of hub price to estimate Equation 19. I use the market average price to maintain consistency with the model set up, though the parameter estimates are robust to using hub prices.

Similar to the discussion in Section 5.1, the identification of most of the cost function parameters stems from temporal variation. I include a firm level fixed effect ϕ_i which accounts for any time invariant spatial differences is productivity. This variation would likely stem from differences in plant characteristics such as fuel type or management strategies. The parameters on environmental and market conditions are identified off the remaining temporal variation of conditions within a location. In particular, the parameter of interest on drought is identified from linking deviations from normal water availability (depicted previously in Figure 4) with changes in plant level production. From the reduced form analyses, it is expected that with worse local drought, production costs increase more for high water use plants than low water use or dry plants ($\rho^{HW} > \rho^L W, \rho^{HW} > \rho^N W$).

Identification of λ_1^j and λ_2^j is more complicated, since P_t is an equilibrium object, and therefore a function of $\varepsilon_{i,t}$. $\varepsilon_{i,t}$ captures idiosyncratic cost shocks, such as unexpected maintenance, but also includes aggregate shocks. While I include a linear year trend and season fixed effects to control for cyclical aggregate shocks, there remains correlation from market wide, one-off shocks such as changes in fuel prices. With cross-sectional correlation in $\varepsilon_{i,t}$, estimates for λ_1^j and λ_2^j will be biased.

To account for this endogeneity I instrument for P_t with total load D_t, estimating the first stage parameters concurrently within the tobit maximum likelihood estimation. Demand is a relevant instrument for price, reflected by the high F-statistics shown in Table 4. Demand is also a valid instrument, as per the discussion in Section 7.1.2, demand is price inelastic. Additionally, within a period the factors that affect supply costs, such as labor and fuel costs, are generally unlikely to directly affect demand as well. The main risk to demand being a valid instrument comes from concern about the aggregate shock part of $\varepsilon_{i,t}$ being autocorrelated. As shown in Equation 11, demand gradually responds to prices meaning 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 $\varepsilon_{i,t}$. I will argue that this channel of bias is likely quite weak, since determination of demand is dominated by seasonality and temperature variation. Regressing D_t on a linear year trend, month fixed effects, and a quadratic in average monthly temperature results in an R^2 value of 0.944. The high explanatory power of these seasonal, exogenous variables leaves relatively little room for robust correlation with the aggregate shock.

The estimated cost parameters are presented in Table 4. The first line of the table shows the estimates of λ_2^j for each technology type, reflecting the curvature of the cost curve with respect to generation. The first column shows that this parameter is significantly larger for high water use plants than low water use or dry, suggesting that they are relatively price inelastic as increasing production is very costly. Additionally, using the full set of cost parameters to compare the average estimated marginal cost of production for each plant type shows that high water use and low water use plants have significantly lower marginal costs than dry cooled plants. Under merit order operation, these comparative costs would place high water and low water use plants as baseline plants that come online first, while the more expensive dry cooled plants would 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 for high water use plants, but not others. For high water use plants, moderate to severe drought increases marginal production costs by \$20.9/MWh while extreme drought increases costs by \$51/MWh. Compared to an average wholesale price of \$35/MWh, these estimates reflect substantial increases in operating costs. In contrast, drought conditions have a smaller impact on production costs for low water use and dry cooled plants.

8.2 State Transition Parameters

Estimating investment costs relies on the parameters dictating the transition of state variables over time (Equations 7-12), which I estimate separately using the available data for plants in ERCOT from 2000 through 2022.[17] For the environmental variables temperature, drought, and renewable capacity factors, I estimate the parameters using ordinary least

[17]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 4: Cost Function Parameters

	High Water	Low Water	Dry
Capacity used: λ_2^j	347.83	347.83	269.65
	(209.37)	(209.37)	(57.02)
Moderate-Severe: β_1^j	11.89	4.10	4.52
	(11.45)	(3.32)	(2.27)
Extreme: β_2^j	30.34	8.62	12.01
	(16.84)	(4.59)	(3.93)
Average cost per MWh	14.63	3.82	48.96
F-stat	571	571	670
Observations	12,088	12,088	15,000

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. Bootstrapped standard errors are shown in parentheses.

squares with time-series of location specific variables. For the market variables nuclear generation, quantity demanded, and prices I again use ordinary least squares with market level time-series data. Note in particular that I use the monthly average wholesale price observed in the data to estimate the parameters for Equation 12.

Using the data on prices to estimate the transition parameters is internally consistent under the assumption that the modeled equilibrium prices respond to the state variables in the same way as real prices do. Counterfactual changes to the model's price generating process, such as through changing the generation mix, may invalidate this assumption. For example, forcing worse drought conditions in the model could reduce the amount of high water use capacity potentially leading to a weaker relationship between market average drought and wholesale prices. This sort of dynamic would result in the transition parameters estimated using the data to become inconsistent with the model. Therefore, when examining counterfactual scenarios, I re-estimate the transition parameters for Equation 12 using simulated price data to maintain internal consistency.

I follow the process presented by Lee and Wolpin (2006) to re-estimate the transition parameters for the counterfactual analyses. 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 solve for equilibrium prices. Third, I use the simulated prices to re-estimate the transition parameters for Equation 12. 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.

8.3 Investment Costs

I use the plant first order condition from Equation 6 to estimate the linear ($\delta_1^{j,l}$) and quadratic (δ_2^j) cost parameters, as well as the distribution of idiosyncratic investment cost shocks (σ_ν^j). Under Equation 6, the optimal level of new capacity investment is a linear function of expected future marginal profits, $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, P_t, K_i^*)]$, and an idiosyncratic investment cost shock, ν_i. I assume that ν_i is normally distributed i.i.d. mean zero, and additionally that it is uncorrelated with the subsequent production shocks faced by the firm, and therefore unrelated to the expected future marginal profits. By Equation 17, profit each period is linear in K_i, so that in combination with independence from the error terms $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, P_t, K_i^*)]$ is exogenous. Regressing K_i on $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, P_t, K_i^*)]$ following Equation 6 should therefore return unbiased estimates of $\delta_1^{j,l}$ and δ_2^j. I estimate the parameters separately for each technology type to allow for cost heterogeneity reflective of differential infrastructure needs. Additionally, due to potentially thin samples within each climate division, I cluster divisions into three larger regions (west, east, and south) and estimate a unique linear investment cost for each larger region.

I first numerically solve for $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, P_t, K_i^*)]$ for each plant. To do so, I simulate a series of state space and wholesale price draws using the state transitions outlined in Section 7.1.2 and estimated as described above. For each period of the simulated series, I use the simulated price and states to calculate firm level marginal profits. I then collapse the series of marginal profits into the discounted sum over the plant's lifespan. To define a plant's lifespan, I calculate the average age of retired plants from the US sample of power plants for each technology type. This process returns a lifespan of 20 years for non-thermals, 60 years for high water use, 43 years for low water use, and 30 years for dry. I assume an annual discount rate of $\beta = 0.95$. I repeat the simulation process with new state and price draws 1,000 times, and average over the results to get a plant level estimate of $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, P_t, K_i^*)]$.

I measure capacity investment in the data as the plant level total of new capacity construction since 2000. This includes both construction of new plants and investment in existing plants. I combine both types of investment to increase power since construction of new plants can be relatively rare depending on the technology type. The validity of this process relies on the assumption that marginal investment costs are identical across the two settings and that under both there are no fixed investment costs. I restrict to investment since 2000 since technological change likely makes historic investment inconsistent with modern investment costs.

Two challenges for estimation arise from censoring of investment at zero. First, since observed investment in capacity must be non-negative, the capacity measured in the data reflects a censored version of the true optimal capacity from Equation 6. I account for this by using a tobit regression estimated with maximum likelihood and 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 sort of sample selection could lead to biases in the estimated cost parameters by ignoring a relevant subsample of plants. To address this, I construct a set of "never-constructed" plants that are incorporated into the sample. For each technology type and location I include 100 of these plants (resulting in 4,000 plants total). Each of the "never-constructed" plants is recorded as having zero capacity investment and has expected marginal profits constructed following the same process as for the real plants.

The estimated investment cost parameters are shown in Table 5. 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 dry cooled plants, with 250 MW of capacity costing $XX million. 250 MW of non-thermal capacity in contrast costs $169 million, while comparably sized high water use and low water use thermals would cost $575 and $1,655 million respectively. 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. Additionally, the per MW investment cost of the median investment is quite similar to construction cost estimates from the EIA for approximately comparable plants for all but low water use plants, as shown in the last two lines of the table.[18] It is reasonable that costs do not match perfectly, since there are additional costs to plant construction beyond the physical construction costs such as siting permits or community negotiations.

[18]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: Investment Cost Parameters

	Non-thermals	High water use	Low water use	Dry
Linear cost: $\delta_1^j/1{,}000$				
West	1,540	5,049	2,681	1,997
	(.)	(.)	(.)	(.)
East	1,709	4,977	4,031	2,288
	(.)	(.)	(.)	(.)
South	1,950		3,259	1,882
	(.)	(.)	(.)	(.)
Quadratic cost: $\delta_2^j/1{,}000$	1.4696	0.0805	-0.3628	-0.7477
	(.)	(.)	(.)	(.)
Cost shock standard deviation: $\sigma_\nu^j/1{,}000$	725	388	1,316	413
Estimated cost per MW (millions)	1.76	5.12	2.35	2
EIA cost per MW (millions)	1.4	1.1-2.7	1.1-2.7	0.5

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. Bootstrapped standard errors are shown in parentheses.

9 Counterfactual Drought Scenarios

This section presents counterfactual analyses, simulating investment and production in ERCOT under alternative climate scenarios. I use drought projections from two different emissions scenarios to simulate alternative climate futures. For both scenarios, I simulate the equilibrium generation mix as well as wholesale energy prices. These simulations allow me to both make predictions about the risk from future climate change (the third research question) and test Hypothesis 5 from the stylized model, that endogenous investment may mitigate drought shocks.

I model future drought conditions using estimated drought index PDFs calculated by Zhao and Dai (2022) under two alternative climate possibilities.[19] 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.[20] 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 recognizes the initial heterogeneity in environmental conditions. I keep the transition parameters for drought and the other non-price state variables the same as estimated in the data. Without a more detailed climate model or model of demand, I cannot reliably estimate the changed

[19]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.

[20]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.

relationships between drought, temperature, and demand. 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.

Under the two alternative futures, I simulate the equilibrium generation mix and wholesale prices. I simulate capacity choices for the set of potential plants with the initial investment period occurring in January 2010. These choices return the equilibrium generation mix. I then simulate series of state variables and wholesale prices using the simulated generation mix and alternative drought distributions. I compare the average wholesale price during non-drought periods across the different scenarios to capture the price impact of the shift in generation mix due to drought. If changed environmental conditions increases investment in non-thermal plants prices should decrease, while if investment in dry plants increase prices should also increase. I then use the price series to re-estimate Equation 2 to examine how much of the drought shock is mitigated by adaptive investment.

The equilibrium generation mix under the counterfactual climate scenarios are shown in Table ??, with each row measuring the share of total capacity belonging to each technology type. The first column shows the mixture under the historic PHDI distributions estimated in the data, representing a world without climate change. The second column shows the low-to-moderate emissions scenario, while the third column shows the high emissions scenario. Across both climate change scenarios, investment in high water use technologies is decreasing with emissions, in line with the theoretical framework and reduced form analyses. Investment across the other three technologies increases, with a 3% increase for non-thermals and a 20% increase for both low water plants and dry cooled.

The alternative generation mixes give rise to somewhat higher wholesale prices during non-drought conditions, but mitigate drought driven price shocks. The average price during market average non-drought and drought conditions are shown in the first two rows of Table ??. Since the retail electricity prices that consumers pay are a function of wholesale energy prices, having higher prices in non-drought periods due to adaptive investment is welfare reducing. However, prices being lower during drought periods in the climate change scenarios shows that endogenous investment does help mitigate the price shock from droughts. The re-estimated coefficient estimates shown in the subsequent rows show that the impact of drought is significantly reduced. By reducing price volatility, adaptive investment is potentially welfare improving.

10 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 with three empirical research questions. I first look at how drought shocks have previously impacted equilibrium generation and prices. I find that local drought adversely impacts generation from high water use plants, shifting generation towards less water intensive, costlier technologies elsewhere in the market. This shift in generation likely drives a significant increase in wholesale electricity prices, which is welfare reducing for end-use customers. 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 XX. This is welfare reducing/improving because of YY.

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 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.

A.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.[21]

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.

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

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 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.

A.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.

A.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. 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. Figure 4 maps the average scaled PHDI values within each climate divisions in Texas from 2000 to 2023.

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 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.

A.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 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.

Figure A1: Data Availability

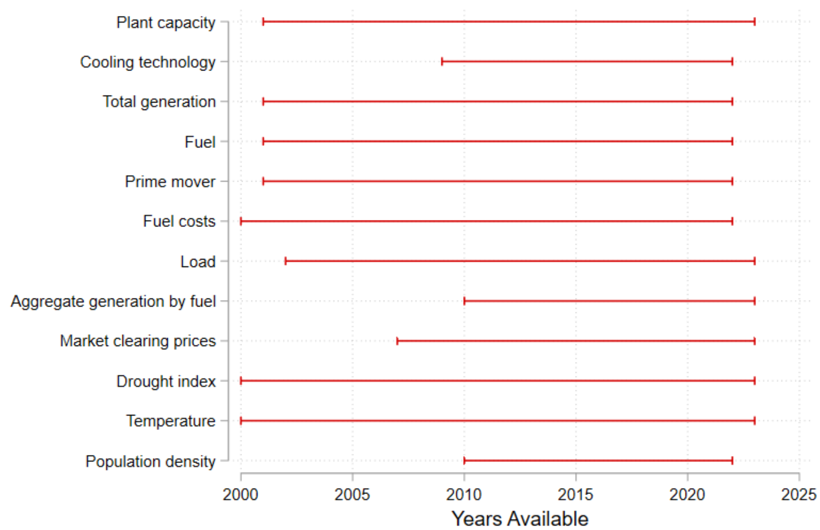

Figure plots the range of time that key variables are available in the raw datasets.

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.

Figure A2: Histogram of PHDI Measure

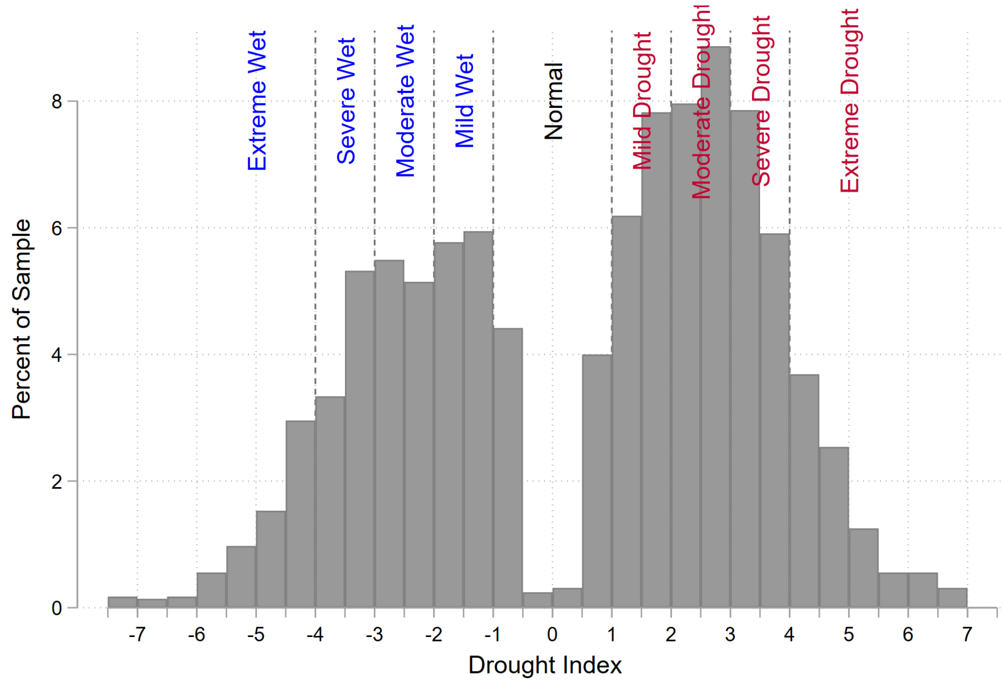

Figure plots histogram of scaled PHDI measures for climate divisions in Texas over 2000 to 2023.

Figure A3: Technology Mix Over Time

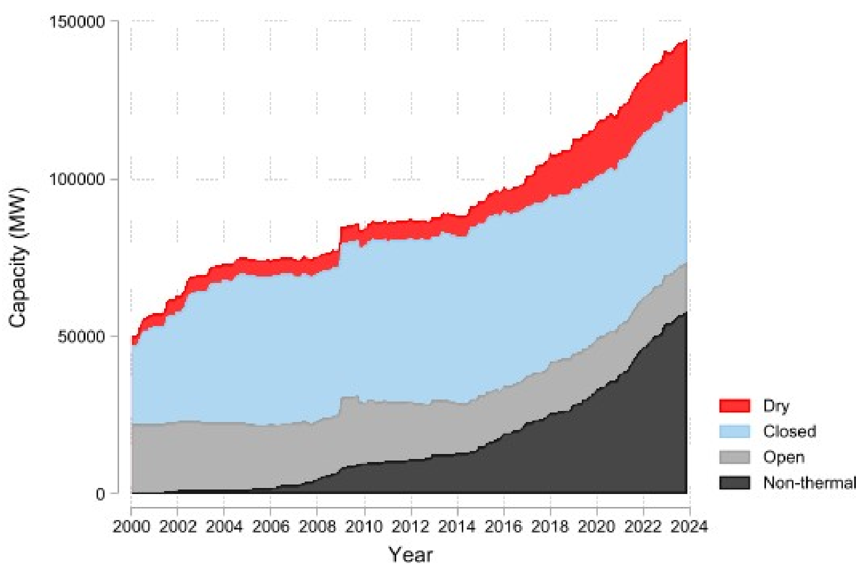

Figure plots total capacity of selected technology groups over time.

Figure A4: Drought Effect on Probability Plant is Capacity Constrained

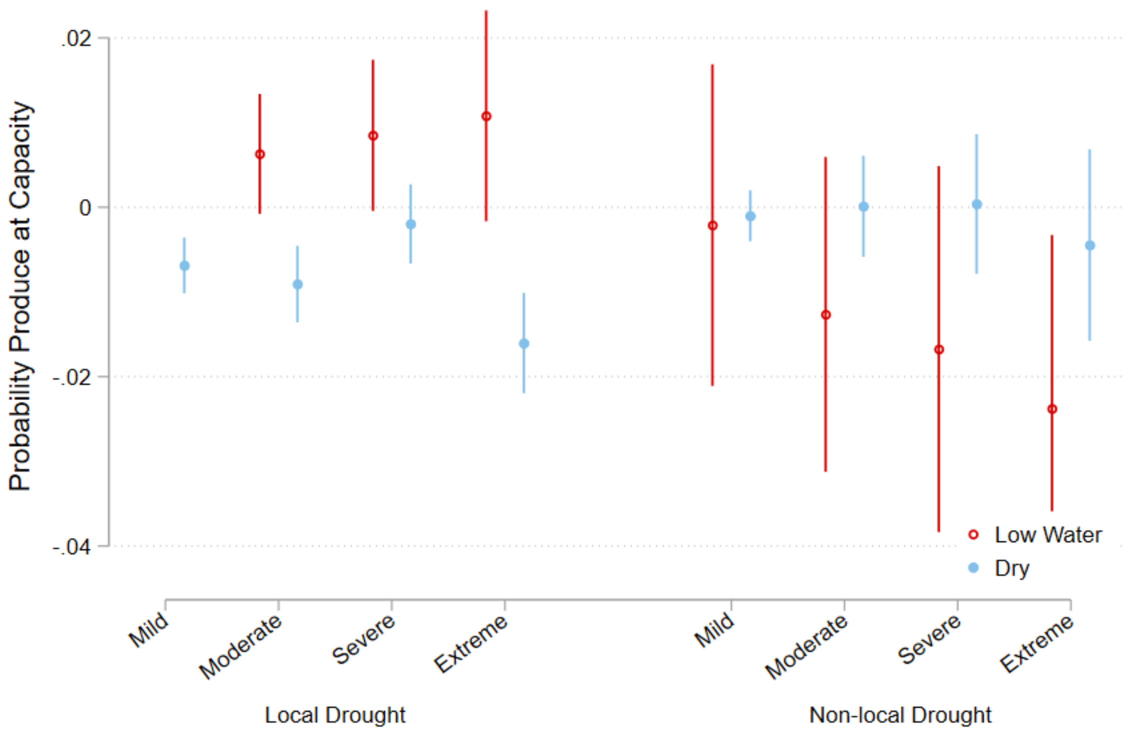

Figure plots marginal effect estimates for the impact of local and non-local drought on the probability a plant is producing at capacity. The analyses are run separately for each of the four technology groups shown in the legend. Non-drought conditions are the omitted category for both local and non-local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

B Spot Market Supplementary Figures and Tables

Table A1: Precipitation Deviation Effect on Share of Capacity Used

	(1)	(2)	(3)	(4)
	High Water	Low water	Dry	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)	(2)
	Levels	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.

Figure A5: Number of Division in Drought Effect on Prices

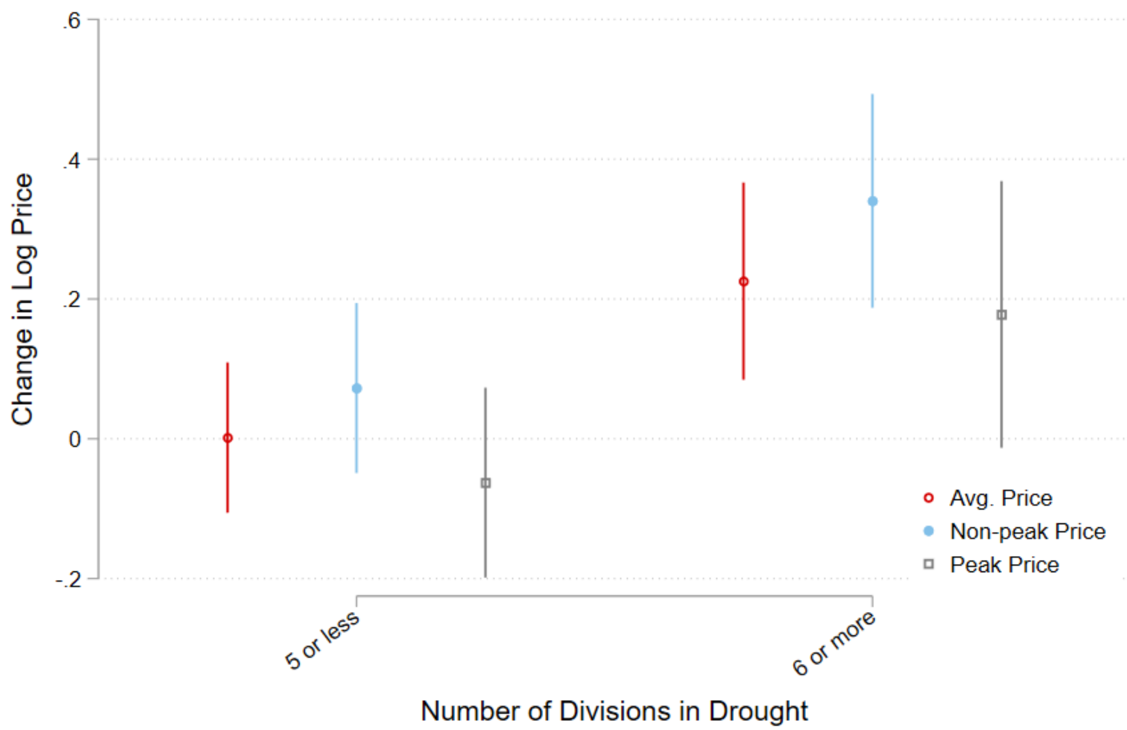

Figure plots coefficient estimates for the impact of the number of climate divisions experiencing at least severe drought on wholesale prices. The analysis is run separately for each of the three prices shown in the legend. Zero climate divisions in severe drought is the omitted category. Standard errors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

Figure A6: Worst Drought in Market Effect on Prices

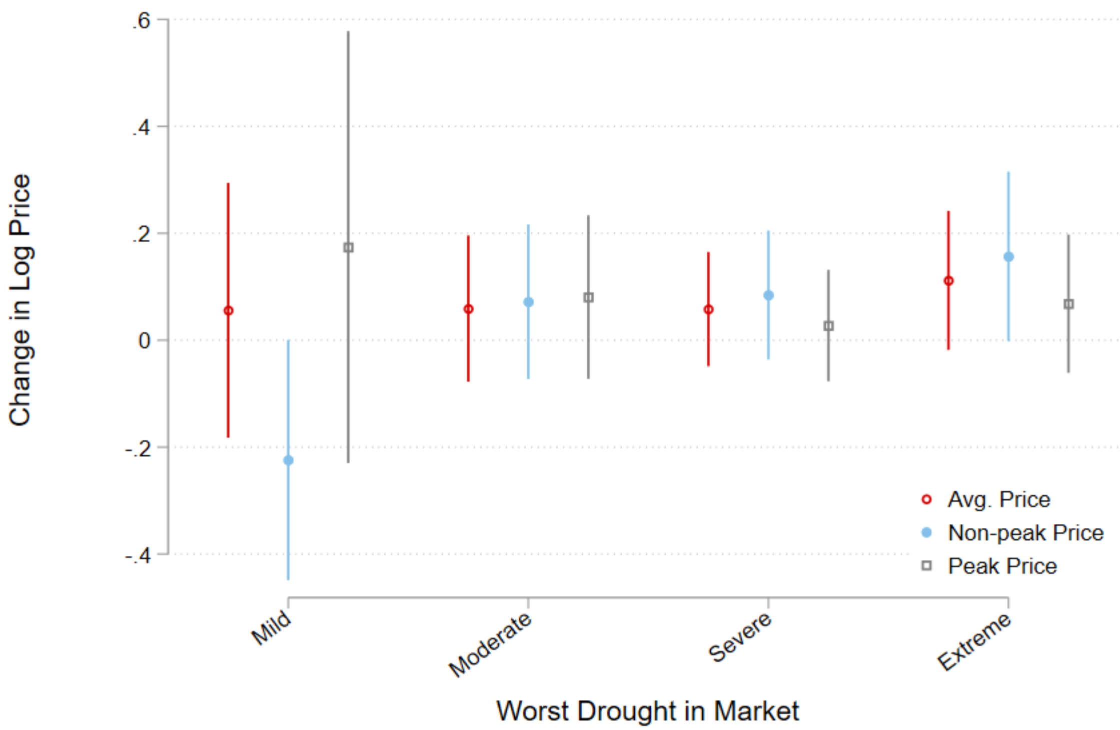

Figure plots coefficient estimates for the impact of the worst drought in the market on wholesale prices. The analysis is run separately for each of the three prices shown in the legend. Zero climate divisions in severe drought is the omitted category. Standard errors are clustered at the plant and month-of-sample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

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 A7: Production Response of Utility Plants

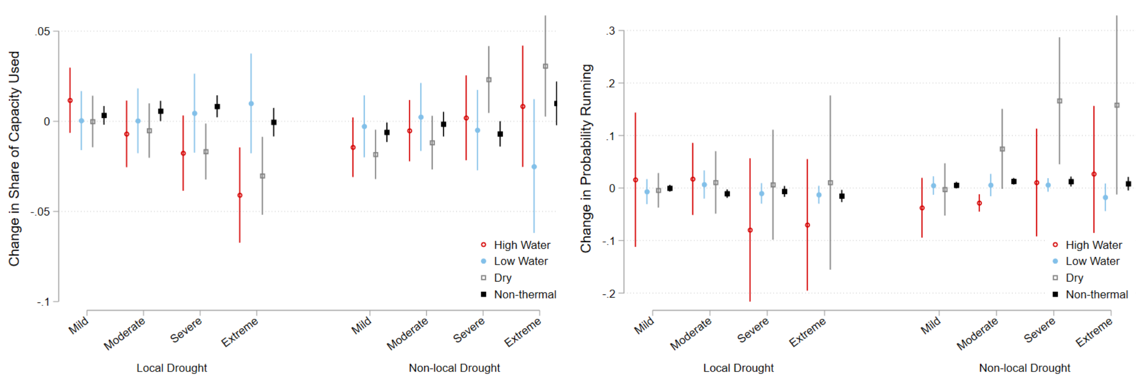

Figure plots marginal effect estimates for the impact of local and non-local drought on the share of capacity used and the probability a plant is running, for the subset of plants owned by a utility. The analyses are run separately for each of the four technology groups shown in the legend. Non-drought 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 A8: Production Response of Non-cogeneration Plants

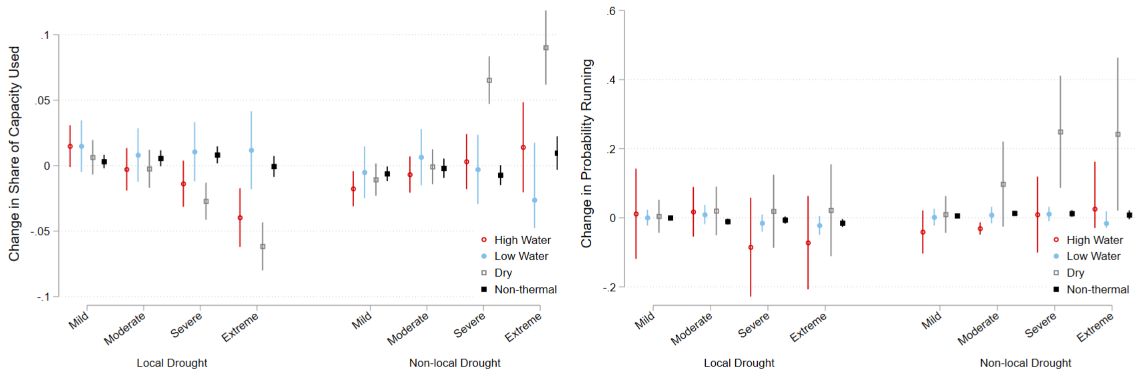

Figure plots marginal effect estimates for the impact of local and non-local drought on the share of capacity used and the probability a plant is running, for the subset of plants that are not combined heat and power plants. The analyses are run separately for each of the four technology groups shown 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 A9: Production Response During Non-Summer Months

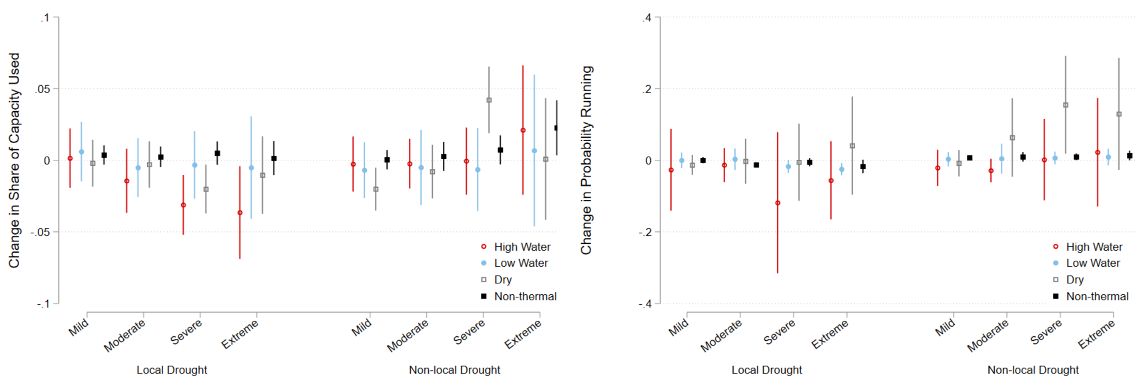

Figure plots marginal effect estimates for the impact of local and non-local drought on the share of capacity used and the probability a plant is running, for the subset of observations not occuring June through September. The analyses are run separately for each of the four technology groups shown in 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 A10: Drought Effect on Non-Summer Wholesale Prices

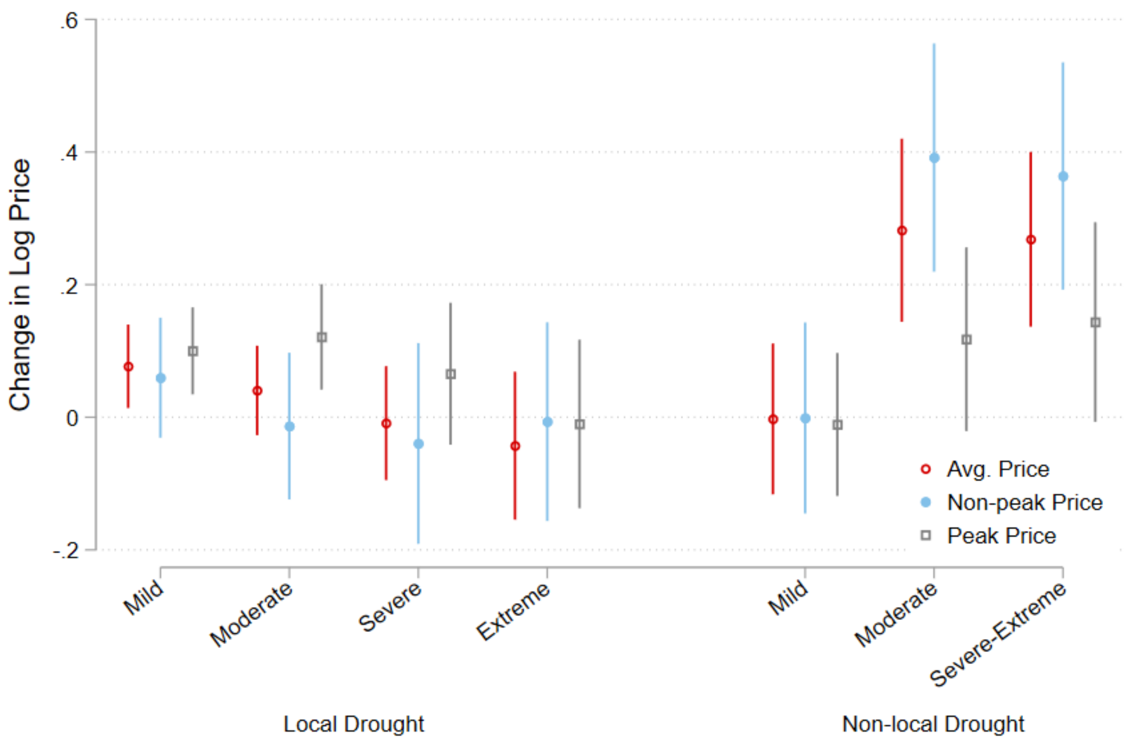

Figure plots coefficient estimates for the impact of local and non-local drought on wholesale prices in non-summer months. The analysis is run separately for each of the three prices shown in the legend. Non-drought conditions are the omitted category for both local and non-local drought. Standard errors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

Table A6: Share of Generation Capacity Used Pre- and Post-2010

	High water use		Low water use		Dry		Non-thermal	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Local drought								
Mild	0.018	0.017	0.009	-0.018	0.012	-0.018	0.005	-0.018
	(0.023)	(0.014)	(0.017)	(0.015)	(0.013)	(0.015)	(0.008)	(0.015)
Moderate	-0.009	-0.002	0.006	-0.004	0.009	-0.004	0.006	-0.004
	(0.017)	(0.014)	(0.015)	(0.018)	(0.021)	(0.018)	(0.004)	(0.018)
Severe	-0.020	-0.001	0.006	-0.001	-0.016	-0.001	0.009*	-0.001
	(0.021)	(0.019)	(0.009)	(0.022)	(0.039)	(0.022)	(0.005)	(0.022)
Extreme	-0.054*	-0.006	0.010	0.019	-0.040	0.019	0.001	0.019
	(0.031)	(0.011)	(0.011)	(0.031)	(0.062)	(0.031)	(0.009)	(0.031)
Non-local drought								
Mild	-0.029	0.011	-0.001	-0.014	-0.024	-0.014	-0.002	-0.014
	(0.032)	(0.018)	(0.008)	(0.013)	(0.015)	(0.013)	(0.004)	(0.013)
Moderate	-0.014	0.046***	0.015	-0.032**	0.005	-0.032**	0.005	-0.032**
	(0.032)	(0.004)	(0.013)	(0.016)	(0.017)	(0.016)	(0.005)	(0.016)
Severe	-0.007	0.028***	0.011	-0.046**	0.061	-0.046**	-0.003	-0.046**
	(0.044)	(0.007)	(0.013)	(0.020)	(0.039)	(0.020)	(0.007)	(0.020)
Extreme	0.003	0.002	-0.006	-0.024	0.080	-0.024	0.014	-0.024
	(0.026)	(0.025)	(0.016)	(0.027)	(0.054)	(0.027)	(0.010)	(0.027)
R-squared								
Observations	2,466	1,940	9,761	5,974	15,002	5,974	25,126	5,974

Table presents marginal effect estimates for the impact of local and non-local drought on the share of capacity used. The analyses are run separately for each of the four technology types and for each time period (pre-2010, post-2010). 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 A7: 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.

C Investment Supplementary Figures and Tables

Table A8: Probability of Mothballing

	(1) High Water	(2) Low Water	(3) Dry	(4) Non-thermal
Mean PHDI last 2-10 years	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)
Fixed effect				
Outcome Mean	0.08	0.04	0.05	0.03
Observations	36,390	49,602	518,470	464,823

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 A9: Probability of Retirement

	(1) High water use	(2) Low water use	(3) Dry	(4) Non-thermal
Mean PHDI last 10 years	0.646	-0.634	-0.094	-0.557
	(3.985)	(0.716)	(0.234)	(0.399)
Observations	196,286	207,309	931,485	605,705

Table presents correlations between standardized average previous drought conditions and the probability that an operating thermal plant is retired. Analysis is run separately for each thermal technology using a Cox hazard model, stratified by climate division and conditional on plant operating year. Standard errors are shown in parentheses and clustered at the climate division level.

Table A10: 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 A11: Technology Choice for Constructed Plants by Fuel

	High water use		Low water use		Dry	
	(1)	(2)	(3)	(4)	(5)	(6)
	Natural gas	Coal	Natural gas	Coal	Natural gas	Coal
Mean PHDI 10 years before	-0.057	0.154	0.042	-0.133	0.046	0.000
	(0.050)	(0.148)	(0.040)	(0.156)	(0.029)	(.)
Mean PHDI 10 years after	-0.058	0.101	0.041	-0.074	0.012	-0.000
	(0.070)	(0.145)	(0.045)	(0.153)	(0.023)	(.)
Observations	138,270	61,540	270,225	62,518	282,296	2,783

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.

Table A12: Probability of Mothballing by Fuel

	High water use		Low water use		Dry
	Natural gas	Coal	Natural gas	Coal	Natural gas
Mean PHDI last 2-10 years	0.044***	-0.003	0.031***	-0.016	-0.004
	(0.014)	(0.034)	(0.011)	(0.012)	(0.005)
Mild PHDI last year	-0.001	0.016	-0.012**	-0.010	-0.002
	(0.007)	(0.020)	(0.005)	(0.013)	(0.003)
Moderate PHDI last year	0.019	0.006	-0.008	-0.017	-0.005
	(0.013)	(0.016)	(0.006)	(0.012)	(0.004)
Severe PHDI last year	0.018	0.072	-0.000	-0.021***	-0.004
	(0.019)	(0.066)	(0.008)	(0.008)	(0.005)
Extreme PHDI last year	0.054	0.128	-0.005	0.000	-0.004
	(0.046)	(0.092)	(0.008)	(.)	(0.007)
Fixed effect	Plant	Plant	Plant	Plant	Plant
Observations	15,823	13,579	34,692	8,417	221,991

Table presents correlations between standardized average previous drought conditions and the probability that an operating thermal plant is mothballed. Analysis is run separately by technology and fuel. 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 A13: Probability of Retirement by Fuel

	High water use		Low water use		Dry
	(1)	(2)	(3)	(4)	(5)
	Natural gas	Coal	Natural gas	Coal	Natural gas
Mean PHDI last 10 years	-0.718***	0.040	0.025	0.234*	0.083
	(0.221)	(0.138)	(0.192)	(0.133)	(0.078)
Observations	63,720	115,369	109,283	85,422	406,356

Table presents correlations between standardized average previous drought conditions and the probability that an operating thermal plant is retired. Analysis is run separately by technology and fuel using a Cox hazard model, conditional on plant operating year. Standard errors are shown in parentheses and clustered at the climate division level.

Table A14: New Investment Share by Technology

	(1)	(2)	(3)	(4)
	High water	Low water	Dry	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.

Figure A11: Water Consumption by Technology

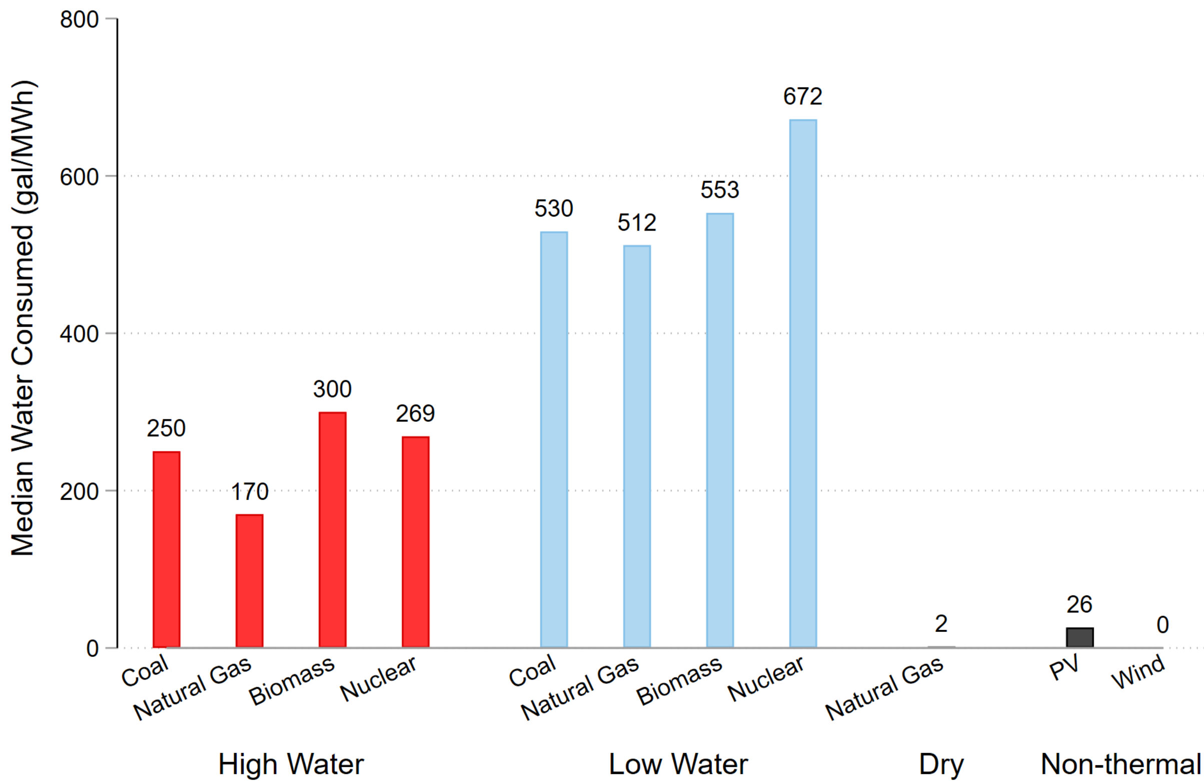

Figure plots the median volume of water consumed per Kwh of electricity produced. The x-axis categories disaggregate by cooling technology and fuel type. Values are collected from Macknick et al. (2011).