Climate Change and Endogenous Investment in Electricity Markets

Lena Harris*

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Abstract

Quantification of preemptive adaptation is necessary for accurate predictions of damages from climate change. This paper provides novel estimates of the efficacy of preemptive, technology based adaptation at reducing climate change damages in the context of the Texas electricity market. To do this, I estimate a model of investment and production which is unique in incorporating local temperature and drought as determinants of production costs. I then use the model to construct counterfactual markets under alternative climate futures, with and without endogenous adaptation. The results indicate that firms respond to changing environmental conditions by changing the types of technologies used to generate electricity. This adaptation has a net benefit ranging between \$212 billion and \$1.1 trillion, stemming primarily from preventing significant increases (up to 250%) in wholesale energy prices that would otherwise occur.

JEL Classifications: L23, Q40, Q41, Q54

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1 Introduction

Climate focused policy decisions often rely on quantifications of damages due to changing environmental conditions. These estimated damages must account for both preemptive and responsive adaptations, since ignoring these adaptations could grossly misstate the true damages. However, it is often difficult to quantify the effectiveness of adaptation, in particular preemptive technological adaptation, at reducing climate change damages. Analyses attempting to do so face identification challenges due to the gradual nature of changes in both climate and behavior. This identification challenge has resulted in there being little empirical evidence which holistically quantifies the efficiency of technology-based adaptation decisions, accounting for benefits, costs, and externalities.

This paper helps fill this gap in knowledge by quantifying the efficacy of preemptive adaptation at reducing climate driven damages in the context of the Texas electricity market. The Texas electricity market is dominated by thermal electricity generation (e.g. coal and natural gas). These plants may be negatively impacted by increased temperatures and drought under climate change, depending on their location and production technology. Specifically for technology, a plant's cooling system dictates the water-intensity and efficiency of production. With climate change expected to increase temperatures and drought risk in Texas (World Bank Group, 2026), firms may preemptively adapt by relocating plants or switching to less susceptible technologies. This adaptation may mitigate future profit loss for the plants due to climate shocks, but due to the technology choice trade-off between efficiency and exposure to shocks, plant adaptation may lead to higher consumer energy prices and increased emissions from the grid.

I use an empirical model of plant level investment and production to run counterfactual simulations under two alternative climate futures, SSP2-4.5 and SSP5-8.5 from CMIP6. For each scenario, I compare average firm revenues, wholesale energy prices, total investment costs, and estimated CO_2 emissions to a historic climate scenario to estimate adaptation benefits, costs, and externalities. I find that endogenous adaptation significantly increases the total cost of investment in the grid, however this increased cost is significantly offset by consumer gains from lower energy prices. Over a horizon of 50 years, I estimate the undiscounted net benefit of adaptation to range between $212 billion and $1.1 trillion depending on the climate future. Additionally, I examine variation in adaptation behavior across environmental changes. Existing literature on climate and electricity markets often focuses exclusively on temperature change or drought shocks, but my results highlight the importance of accounting for correlated changes in these environmental conditions.

I first establish that drought is a relevant environmental shock for electricity markets, shifting spot market production away from high water use plants. I expand 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). Since Texas has very little hydroelectric generation ($< 0.1\%$ of generation), this analysis is able to isolate the direct impact on thermal production exclusive of equilibrium changes due to hydroelectric production shifts (Eyer and Wichman, 2018; Qiu et al., 2023). Combining plant level production and price data with plausibly exogenous drought conditions, I find that firsthand exposure to a worse drought shock reduces generation from high water use plants. Dry cooled plants increase generation in response to worse market wide drought, highlighting the importance of market equilibrium in determining drought damages. These results align closely with similar findings from Hutchens et al. (2026). The drought-driven changes in generation are associated with about a 30% increase in wholesale energy prices. A novel finding is that there are larger price effects during non-peak hours when quantity demanded is low (McDermott and Nilsen, 2014), indicative that the available technology mix is important for determining the total price effect.

I then develop a model of investment and production to facilitate the counterfactual analyses. Modeled 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 exogenously 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 future environmental exposures. There are four unique technology types: high water use, low water use, and dry thermals and non-thermals (i.e. wind and solar).[1] Capacity investments

[1]Hydroelectric and nuclear are excluded from the technology set. This is because there is negligible hydroelectric generation and investment in nuclear capacity in Texas.

are made to maximize plants' expected sum of discounted profits, less the associated investment costs. Production each subsequent period is subject to location specific environmental shocks and the capacity constraint determined by the investment decision. Non-thermal production is exogenously determined, while thermal firms choose optimal production subject to production costs which are a function of both local temperature and drought.

I estimate the model 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 estimate the parameters with a Tobit regression, instrumenting for price on the right hand side with aggregate demand (Bushnell, Mansur, and Saravia, 2008). The parameter estimates indicate drought increases production costs by up to \$35/MWh for high water use plants, but has no meaningful impact on other thermal plants. Increased temperature is only meaningful for dry cooled plants, and leads to lower production costs. For investment costs, I use the plants' first order condition to solve for optimal capacity investment as a function of the plants' expected future marginal profit flows. The resultant parameters are in line with existing engineering estimates and other econometrically identified estimates, with the important feature that more infrastructure intensive, low water use plants are significantly more expensive per MW of capacity than the other technologies.

This paper contributes to the literature on climate change adaptation by providing a novel quantification of the value of technology based adaptation in a non-agricultural setting. Within this broad literature, there is a significant body of work examining technology-based, preemptive adaptations with respect to agriculture (Burke and Emerick, 2016; Emerick et al., 2016; Aker and Jack, 2021; Hultgren et al., 2022; Moscona and Sastry, 2023). Beyond agriculture though, the literature discusses technologic adaptation almost exclusively in the context of heat mortality (Carleton et al., 2022; Barreca et al., n.d.). The remaining literature focusing on industrial production considers preemptive adaptation specifically through the lens of migration, either with respect to individuals (Boustan, Kahn, and Rhode, 2012; Patel, 2023; Cruz and Rossi-Hansberg, 2024), investment (Indaco, Ortega, and Taṣpınar, 2021; Bilal and Rossi-Hansberg, 2023; Balboni, 2025; Jia, Ma, and Wenxin Xie, 2026; Castro-Vincenzi, n.d.), or production network (Pankratz and Schiller, 2024; Castro-Vincenzi et al., 2024). Additionally most of the literature for industrial adaptation focuses on disaster risk (i.e. floods) or temperature changes, largely ignoring drought. While my analyses incorporate adaptation through spatial sorting, I focus primarily on how endogenous changes in production technologies impact market outcomes.

This paper also builds on the literature specific to climate change and electricity markets as the first to examine endogenous supply side investment. The demand side of this literature primarily investigates the spot-market consequences of increased demand in response to increased temperatures (Aroonruengsawat and Auffhammer, 2011; Auffhammer, Baylis, and Hausman, 2017). The supply side of the literature can be seperated into two distinct categories. The first uses retrospective analyses to estimate the impact of historic drought shocks on an exposed, fixed set of plants. This work generally focuses on drought induced reductions in hydroelectric production, which in turn spur increased production from thermals (Gleick, 2017; An and Zhang, 2023; Qiu et al., 2023; Bagnoli et al., 2025; Lee, Balza, and Belmar, n.d.), though there is also work more focused on the thermal production impacts (Scanlon, Duncan, and Reedy, 2013; Herrera-Estrada et al., 2018; Eyer and Wichman, 2018; Mamkhezri and Torell, 2022; Hutchens et al., 2026). 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, the second 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 et al., 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 novel evidence that drought results in technological adaptation (Chen, Fu, and Chang, 2021; Bagnoli et al., 2025).

2 Generation Technologies and ERCOT Overview

2.1 ERCOT Market Structure Overview

The analyses focus on the Electricity Reliability Council of Texas (ERCOT), which has several features making it an attractive setting. First, ERCOT is a large market both in terms of transaction volume and spatial area, serving 26 million consumers across Texas. Second, it is isolated from other grids, limiting the impact of imports or shocks to systems outside of Texas.[2] Third, within ERCOT there is negligible hydroelectric generation, ruling out indirect effects of temperature and drought shocks on thermal generation through equilibrium impacts due to changes in hydroelectric generation.[3] Lastly, ERCOT was restructured in 1999, and while there is some evidence of strategic behavior in this market, it is largely considered to be competitive (IMM, 2023; Woerman, n.d.).[4]

The market operates through an auction framework, with the end result that power plants sell electricity to the grid and receive a common price, which is determined by the operating costs of the marginal plant that fills demand. The auction structure also results in plants operating in order of least cost. This means that in periods of low (high) demand, the marginal plant is relatively low (high) cost leading to a lower (higher) wholesale price.[5] More detailed information on the market structure is available in Appendix Section A.1.

2.2 Comparison of Alternative Generation Technologies

Power plants rely on different types of technologies to generate electricity, which are subject to trade-offs between their ability to respond to changes in demand, efficiency[6], and water needs. Non-thermal technologies, such as wind and photovoltaic generators, produce energy subject to environmental conditions and are generally considered non-responsive to demand. Thermal technologies on the other hand produce electricity by burning fuel, allowing them to be more responsive to demand. Within thermal generators, there is variation in demand response and efficiency, with the most demand responsive technologies generally also having moderately lower efficiency (EIA, n.d.; Joshi et al., 2020).

How a thermal plant is cooled determines the plant's water needs and impacts the plant's efficiency. High water use plants pull cooling water from a nearby source and then

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

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

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

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

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

return the now warmer water back to the source. By pulling cold water each time, the plant uses minimal energy for cooling but requires a significant amount of water. In contrast, low water use plants reuse the cooling water, reducing water needs but also reducing a plant's efficiency by 2-5% (World Nuclear Association, n.d.). Lastly, plants may be cooled without water (dry) but face larger reductions in efficiency (EPRI, 2002). Table 1 shows that the differences in water needs, as measured by withdrawals, across technologies are significant.[7] More detailed information on generation technologies is available in Appendix Section A.2.

3 Data

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

3.1 Plant Characteristics

Data on power plant locations and characteristics are from the US Energy Information Administration (EIA), form 860. This data covers all plants with at least 1 MW of generating capacity across the US since 2001. For each plant, I observe the plant's location coordinates, total production (nameplate) capacity, modal fuel type, and the year and month that the plant was first operational and retired, if applicable. I define thermal plants as those that primarily use coal, natural gas, or petroleum for fuel and non-thermal plants as those that primarily use wind or solar.[8] I also observe the plant level cooling system since 2009 for plants over 100 MW which I use to classify thermal plants into three water use categories: high, low,

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

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

and dry.[9] Due to data limitations, I drop plants with multiple cooling technologies from my sample and assume that plants had the same technologies pre-2009 as they do post-2009.[10]

Descriptive statistics of the ERCOT market and participant plants are presented in Table 1. Within ERCOT, there are relatively few high and low water use plants in the system. However, these plants have significantly larger average capacities than dry and non-thermal plants, resulting in them accounting for a sizeable share of total generating capacity. Relative to the US at large, ERCOT has relatively more non-thermals, while high water use plants produce relatively little (Table A1).

3.2 Drought Data

Drought and monthly total precipitation data are collected from the National Atmospheric and Oceanic Administration's (NOAA) Climate Division Dataset (Vose et al., 2014). I define drought using the Palmer Hydrologic Drought Index (PHDI) which measures hydrologic drought (ie. changes in stream flows or reservoir levels) on a scale of -10 to 10, with positive numbers reflecting more severe drought and 0 indicating normal conditions.[11] Measuring hydrologic drought in this setting is important since it better reflects the water supplies that are actually available to power plants, compared to simply precipitation or shorter term drought measures.

The PHDI is measured and normalized at the climate division level, where climate divisions are climatically similar areas within the US defined by NOAA (Vose et al., 2014). The normalization process means that drought is interpreted as a deviation away from the climate division's average water availability. Because of this feature of the drought measure, identification for the subsequent analyses stems from cross sectional and temporal differences in the *deviation* of conditions from local normal conditions. Figure 1 presents a visual example of this variation.

[9] "High Water" plants are those with once-through cooling systems, "Low Water" plants are those with recirculating cooling or hybrid (wet and dry) cooling systems, and "Dry" plants are those with dry (air) cooled systems.

[10] Of the 426 Texas thermal plants for which I observe cooling information, only 19 (4.5%) are observed with more than one type of operating cooling system. Similarly, of those with a recorded water source only 7% are documented as using multiple types of water (i.e. surface, municipal, ground, etc.).

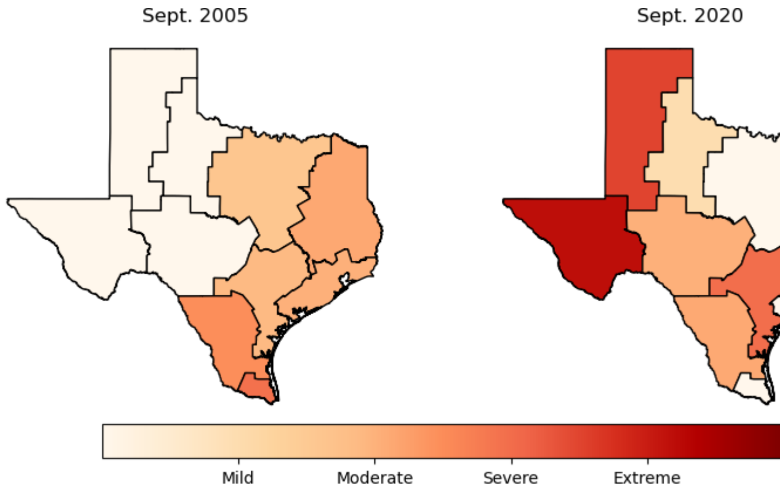
[11] I scale the raw PHDI data by -1 to make worse drought a more positive number for ease of interpretation.

Table 1: Power Plant Characteristics

	Non-thermal	High Water	Low Water	Dry
Panel A: Aggregate Statistics				
Number of plants	403	27	77	261
Percent of total capacity	37	12	38	13
	(0.88)	(0.25)	(0.65)	(0.06)
Percent of total generation	36	4	50	10
	(8.12)	(1.09)	(6.23)	(1.37)
Panel B: Plant Statistics				
Operating year	2015.89	1963.52	1986.00	2008.87
	(6.05)	(12.94)	(20.31)	(17.50)
Age at retirement	12.46	44.80	45.46	25.47
	(3.15)	(9.70)	(14.21)	(17.72)
Mean capacity (MW)	123.41	580.34	674.44	67.51
	(118.68)	(572.99)	(451.22)	(194.01)
Mean generation (GWh)	35.35	77.61	246.89	16.01
	(35.91)	(93.82)	(180.17)	(64.97)
Water withdrawn (gal/MWh)	10.52	29865.22	598.33	2.00
	(12.78)	(9961.53)	(425.71)	
Water consumed (gal/MWh)	10.52	209.57	424.64	2.00
	(12.78)	(59.04)	(279.83)	
Non-zero generation indicator	0.97	0.76	0.97	0.97
	(0.17)	(0.44)	(0.17)	(0.17)
Capacity factor (%)	26.22	12.59	36.34	12.86
	(12.99)	(23.48)	(26.00)	(23.08)

Notes: Table presents descriptive statistics for ERCOT power plants that were operational at any point since 2000. Data is from January to December 2022. Standard deviations, shown in parentheses, are taken over both plants and time. Plant level water withdrawn and consumption are estimated based on fuel type, prime mover, and cooling system (Macknick et al., 2011).

Figure 1: Map of Average Drought



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

3.3 Market Data

The spot market data combines monthly plant level net generation from EIA-923 with ERCOT market demand and prices.[12] For demand, I aggregate hourly data to a monthly measure of market wide load (total quantity delivered). Market average and location specific prices are available in 15 minute intervals since 2010, which I average over time to construct both average and location-specific monthly prices.[13] I also construct peak and non-peak period prices for each month by averaging the 15 minute prices over the peak (2pm to 9pm) and non-peak (9pm to 2pm) hours of demand, respectively.[14]

4 Empirical Evidence of Drought Effect on Production

This section uses data on plant production, prices, and drought in a reduced form framework to document the impact of drought shocks on electricity production. I first show that direct exposure to drought reduces generation from high water use plants, while worse market wide

[12] I drop February 2021 due to an extreme winter storm which resulted in outlier market data.

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

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

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

4.1 Methodology

I regress measures of production and price on two measures of drought. The first measure is drought at the plant's location, $Drought_{l,t}$, defined by the PHDI value in month t for the climate division l where the plant is located. The second is the average drought elsewhere in the market, $\overline{Drought}_{-l,t}$, measured as the average of the PHDI values in month t across the nine other climate divisions in Texas. To allow for non-linearities, I use standard cutoff PHDI values to categorize both drought measures into five bins: no drought, mild, moderate, severe, and extreme.[15] Note that $\overline{Drought}_{-l,t}$ mechanically reflects much more severe total drought than $Drought_{l,t}$, since for $\overline{Drought}_{-l,t}$ to be classified as severe the average of the index across nine climate divisions must be sufficiently high, whereas $Drought_{l,t}$ relies only on conditions in one climate division.

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

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

The vector of covariates $X_{i,t}$ always includes a linear year trend and quadratic in local temperature. For generation outcomes $X_{i,t}$ also includes the wholesale price for the plant's location, instrumented for by total ERCOT load, while for price outcomes $X_{i,t}$ includes the natural log of total ERCOT load. I also include calendar-month, $\phi_{m(t)}$, and climate

[15] 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).

division, ϕ_l, fixed effects to account for seasonality in production and unobserved regional characteristics such as operating expenses or non-market production needs.[16] Standard errors are clustered at the climate division level, based on the level of variation in the drought measure.

For generation outcomes, I use two measures of production $y_{i,t}$ to understand the intensive and extensive changes in generation across technologies. For the intensive margin, $y_{i,t}$ is the share of capacity used, measured as the total amount of energy generated divided by the plant capacity (in 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.[17] For the extensive margin, $y_{i,t}$ is an indicator for positive net generation (i.e. plant is running).[18] 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. I estimate Equation 1 separately for each of the four technology types to allow for greater flexibility in the relationship between the covariates and production outcome measures.

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

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

[17] Because the generation measure is at the monthly level, it is relatively rare that firms are constrained from above. Empirically, 11.8% of the analysis sample is constrained from below, and 0.8% from above. Figure A4 shows the regression results are insensitive to using a linear probability model instead.

[18] 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.

4.2 Identification

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

First, drought could be related to shifts in the demand curve, for example by increasing electricity use for irrigation or by increasing air conditioning use through a positive correlation with temperature (Hoerling, 2018). These correlated demand shifters would act as confounders for estimating the supply side shocks by impacting both prices and production. To account for this potential confounding, I control for the quantity demanded in the price regressions and average wholesale energy prices in the production specification. Note that since generation may influence prices through unobserved, aggregate shocks, I instrument for price with load which is standard in the literature (Bushnell, Mansur, and Saravia, 2008). This instrument is valid since short-run electricity demand is generally considered price inelastic. A more thorough discussion on this is presented later in Section 5.3.2.

Second, there could be confounding from additional drought-related supply shifters, most notably natural gas prices. Natural gas is increasingly mined through water intensive hydraulic fracturing methods, often in Texas, so that drought could simultaneously affect thermal plants' fuel costs in addition to cooling water supplies (Stevens and Torell, 2018). This dynamic may result in upward bias of effect magnitude, since the returned estimates would jointly capture the direct drought effect and a fuel cost effect, and is not easily solved. Because ERCOT is a large consumer of natural gas, changes in ERCOT generation could influence natural gas prices so that controlling for fuel prices would implicitly control away the effect of interest.[19] While I am unable to fully eliminate this source of bias, comparison of the estimated effects across technology types should be relatively unbiased since all technology types rely heavily on natural gas and therefore are subject to the same input price shock.

[19]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, 2025).

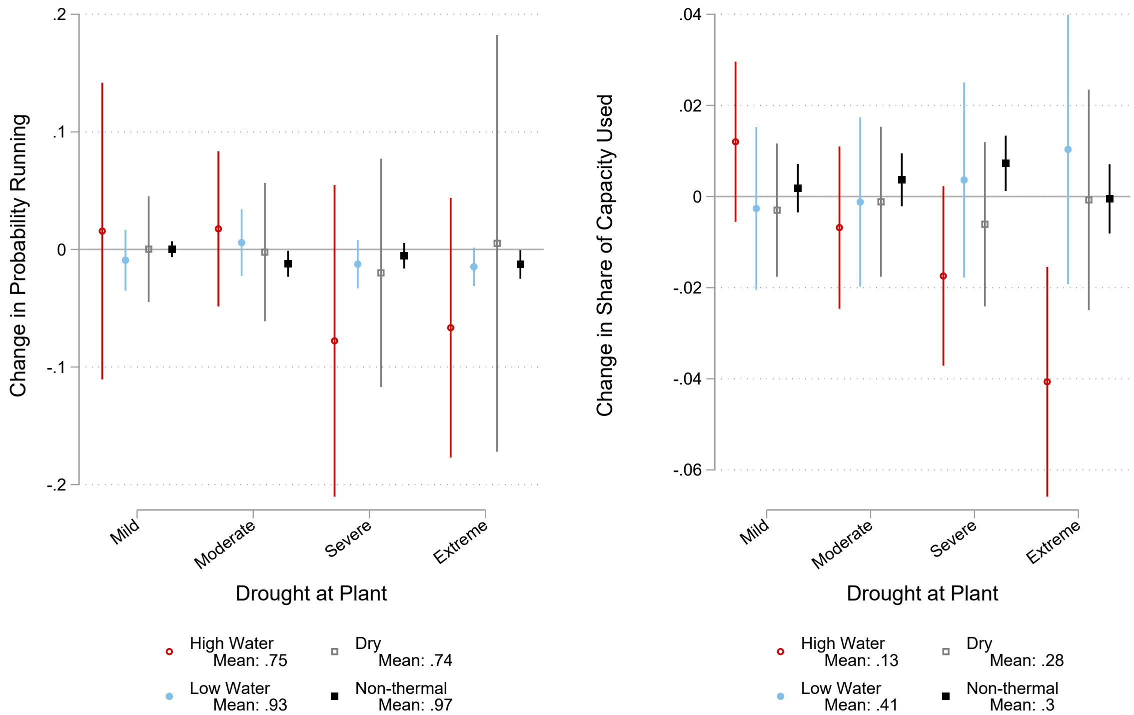
4.3 Results

4.3.1 Generation

Local drought conditions reduce generation from high water use plants but have negligible impact on generation from other technologies. As shown in Figure 2, while there is no statistically significant change in the probability a plant is generating (left panel), the marginal effect estimated for generation as a share of capacity is steadily decreasing with drought severity for high water use plants (right panel). Conditional on the average drought outside of a plant's climate division, entering into severe (extreme) drought reduces the share of capacity used by high water use plants by 1.7 (4.1) percentage points relative to non-drought conditions, conditional on non-zero generation. The average share of capacity used by high water use plants conditional on generating is 17%, scaling the reduction to an economically significant 10% (24%) decrease. For the other technology types, the marginal effect estimates for both the intensive and extensive production margins are fairly stable across drought conditions, reflecting a limited drought effect. These findings show that direct drought exposure is costly for high water use plants but not for less water intensive plants.

Average drought conditions everywhere else in the market instead appear to affect only dry cooled plants, increasing both the probability of generating and the average share of capacity used to generate, as shown in Figure 3. Conditional on the drought inside of a plant's climate division, entering into severe average drought everywhere else in the market increases the probability a dry plant is running by 1.9 percentage points and the share of capacity used by 4.4 percentage points, relative to average non-drought conditions. The average share of capacity used by dry plants when producing is 37%, scaling the level increase to 12%. The marginal effect estimates for the other technologies are again fairly stable across drought severity. It is worth noting that there are small but statistically insignificant increases in the probability that non-thermals are running, a result which could be spurious or may reflect optimizing behavior from non-thermal plants (e.g. timing of planned outages). Overall, these results suggests that in response to market equilibrium changes arising from the adverse impacts of drought on high water use plants, dry cooled plants increase production to substitute for the affected high water use generation.

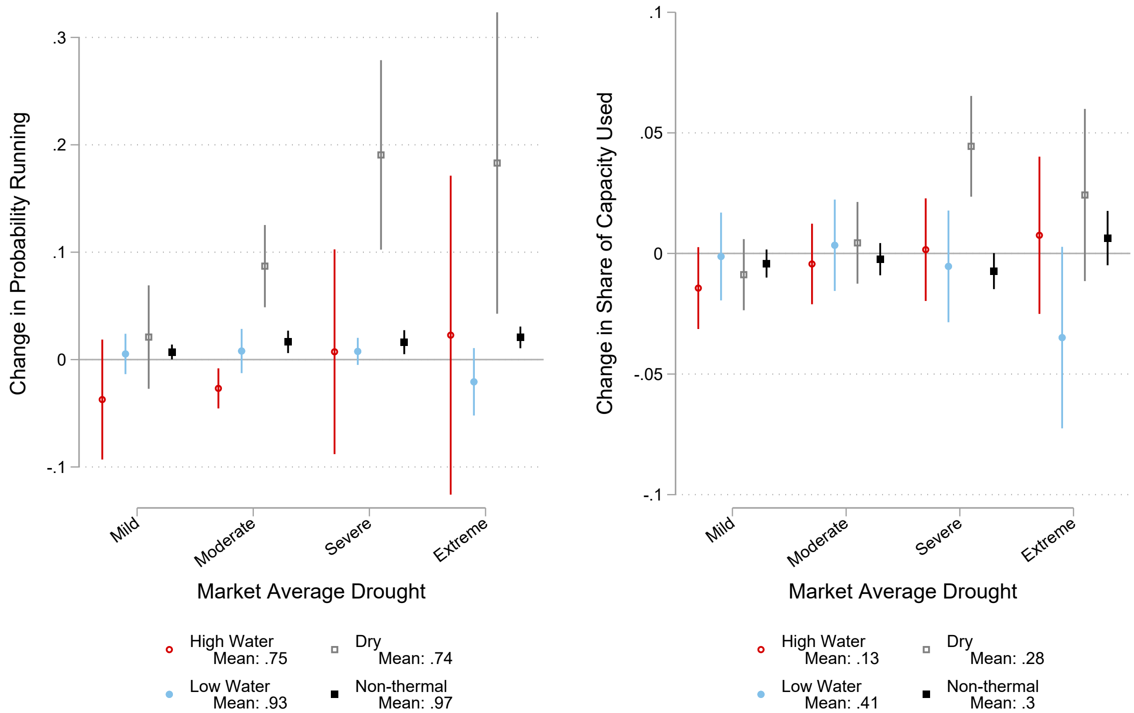
Figure 2: Effect of Drought at Plant Location



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

The results from this analysis roughly align with results from similar analyses in existing work. For example, both Eyer and Wichman (2018) and Mamkhezri and Torell (2022) find relative increases in generation from dry cooled plants during drought conditions in Texas over similar time frames. While direct comparison of estimates is difficult, since these papers only consider local drought conditions, in general my coefficient estimates are significantly smaller in magnitude than theirs. Other analyses looking beyond Texas but following similar plant-level specifications find more of a mixed bag with regard to the effect of local and non-local drought on different technologies, in part because of the equilibrium aspects of drought induced reductions in hydroelectric generation (Eyer and Wichman, 2018; Qiu et al., 2023).

Figure 3: Effect of Average Drought Elsewhere



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

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

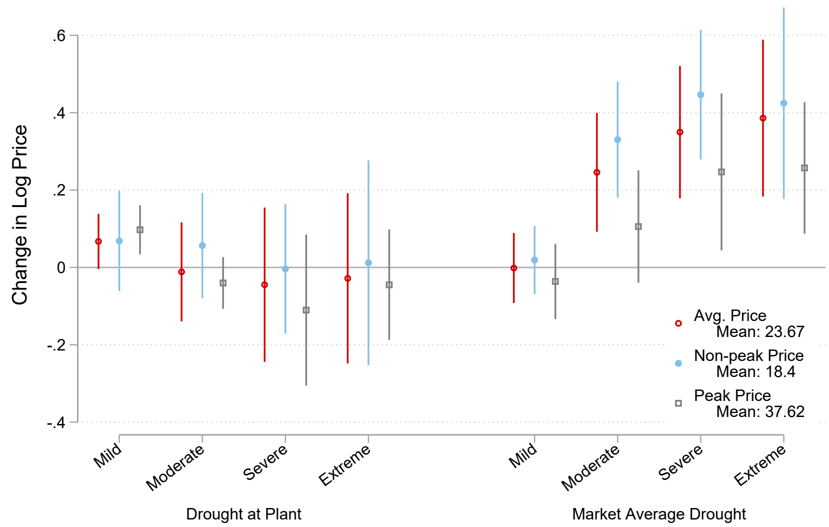
4.4 Prices

There is a limited relationship between local drought conditions and wholesale energy prices. In general, the left of Figure 4 shows that across all price measures the marginal effect estimates are not significantly different from zero. This aligns closely with the isolated impact of local drought on generation: conditional on drought elsewhere in the market, the localized change in output from a few plants is not likely to have a large enough impact on the market to result in significant price changes.

In contrast, there are economically and statistically significant increases in all three wholesale price measures as average drought elsewhere in the market worsens. For instance, the right hand side of Figure 4 shows a 35% 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 \$8.28 increase relative to the mean price of \$23.67. As average drought elsewhere in the market worsens, more high water use plants are potentially being affected leading to a larger shock to aggregate generation. Since the dry cooled plants that come online to replace the lost generation are likely less efficient, the marginal plant filling demand is likely more expensive, pushing prices higher as more substitute production is needed.

Non-peak prices consistently respond to drought more than peak prices, providing evidence that the price effect is driven by the difference in costs of the substitute price-setting plant relative to the original price-setting plant. To explore this dynamic, first consider non-peak hours when demand is low. Since lower marginal cost plants (non-thermals, high water

Figure 4: Drought Effect on Wholesale Prices



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

use, low water use) should be operated first, in periods of low demand without drought the price setting plant is likely a low marginal cost plant. Under a drought shock though, by the previous analyses, generation by dry cooled plants increases so that the new price setting plant is likely a high cost dry cooled plant. Next consider peak hours when demand is high. To meet demand in absence of drought, the price setting firm is likely a dry cooled plant. With a drought shock, the price setting plant is still likely a dry cooled plant. Under the assumption that the difference in marginal costs between two dry cooled plants is less than the difference in marginal costs between a dry cooled and a not dry cooled plant, one would expect to see a relatively smaller increase in prices during peak hours. This is exactly what Figure 4 shows, highlighting the idea that the price effect magnitude is largely determined by the available substitute plants relative to the original price setting plant.

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

4.5 Additional Analyses

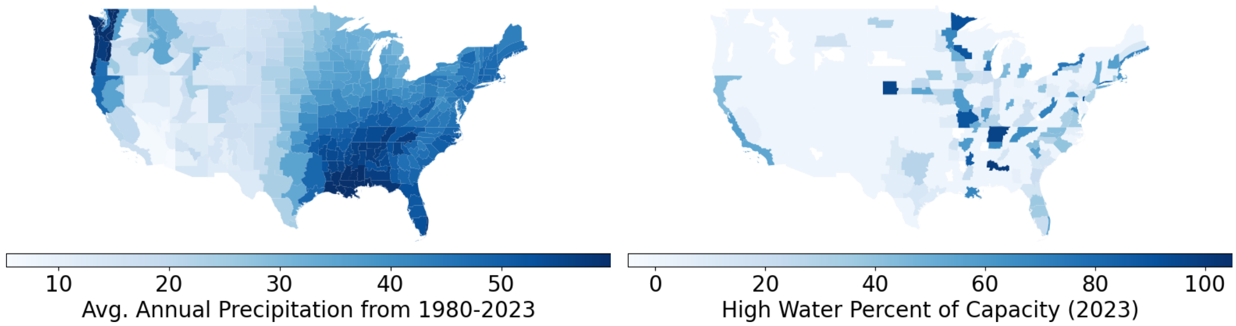
I addition to the above analyses, I also examine several alternative specifications, the results of which are summarized here and presented in more detail in Appendix Section C. I first test several alternative ways to measure variations in water supplies: precipitation, drought duration, and number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

5 Model Framework

This section presents the model of investment and production in ERCOT that will be used to examine the impact of climate change on electricity markets, accounting for adaptation. Existing work projects higher temperatures leading to higher demand (Auffhammer, Baylis, and Hausman, 2017), while the reduced form analyses shown here indicate that more frequent and severe drought shocks will shift production away from high water use plants, both leading to increased wholesale prices. However, the reduced form analysis results also emphasized the importance of generation mix in determining the price effect, which depends on both the directly affected plants as well as the plants that are available as substitutes. This is important since the generation mix may endogenously respond to climate conditions through preemptive adaptation via investment (Bagnoli et al., 2025). Correlational evidence supporting this hypothesis is presented in Figure 5, documenting that the eastern half of the US is both generally wetter than the western half and has a larger share of capacity that is high water use (Averyt et al., 2011). More detailed analyses of this relationship are presented in Section **??**.

The model addresses both endogenous investment and production in response to changing climate conditions by incorporating temperature and drought as determinants of

Figure 5: Maps of Water Availability and Generation Mix



*Notes:*Figure maps average annual precipitation from 1980 to 2023 for each climate division on the left, and the share of generation capacity that is high water use for each climate division as of 2023 on the right.

production costs in the spot market, combining the direct impacts of drought and temperature with the indirect changes working through the generation mix. The remainder of this section presents the model primitives, then works backwards through the market structure, starting with the spot market and ending with investment.

5.1 Model Primitives

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

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

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

Since the main focus of the model is the role of environmental conditions, 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. However, I assume agents have perfect information over the distribution of drought shocks so that no new information is revealed over time, limiting the value of updating investment and allowing me to focus on changes in the equilibrium generation mix. For the generation decision, this modeling choice ignores start-up and ramping costs, though since the model is at a monthly level these costs are likely less relevant. Second, I define all firms in the model as competitive, single plants instead of strategic or multi-plant firms. This modeling assumption is problematic if firms owning multiple plants respond to local environmental shocks 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.

5.2 Spot Market Generation

5.2.1 Non-thermal generation

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

$$q_{i,t}^{NT}(\eta_t, K_i) = \begin{cases} 0 & \text{if } \omega_{l,t} + \phi_i + \varepsilon_{i,t} < 0 \\ (\omega_{l,t} + \phi_i + \varepsilon_{i,t})K_{i,t} & \text{if } \omega_{l,t} + \phi_i + \varepsilon_{i,t} \in [0,1] \\ K_{i,t} & \text{if } \omega_{l,t} + \phi_i + \varepsilon_{i,t} > 1 \end{cases} \tag{2}$$

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

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

$$\pi^{NT}(\eta_t, P_t, K_i) = P_t q_{i,t}^{NT}(\eta_t, K_i) \tag{3}$$

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.

5.2.2 Thermal generation

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

$$c^j(q^j_{i,t}) = \lambda^j_1 q^j_{i,t} + \lambda^j_2 \frac{q^2_{i,t}}{2K_{i,t}} + q^j_{i,t}(\rho^j z_{l,t} + \gamma^j X_{i,t} + \phi_i + \varepsilon_{i,t}) \tag{4}$$

This specification of production costs is microfounded in the regression analyses for the effect of drought on production and prices from Equation 1, and is similar to others in the literature (Reguant, 2014; Butters, Dorsey, and Gowrisankaran, 2025). Costs are non-linear in $q^j_{i,t}$, and in particular dependent on the level of production relative to capacity. I include a set of cost determinants, $X_{i,t}$, similar to those used in Equation 1, consisting of local temperature and its square, a linear year trend and month binaries. I also include permanent productivity differences, ϕ_i, and cost shocks $\varepsilon_{i,t}$. For this specification to accurately reflect plant production costs, I rely on the assumption that the observed market and environmental conditions are sufficient to capture changes in input costs, as well as the assumption that the non-linearities captured by λ^j_1 and λ^j_2 accurately reflect any non-linearities in production costs.

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

Under the cost function in Equation 4, profit maximization leads to the following optimal generation choice for thermal plants,

$$q^j_{i,t}(\eta_t, K_i) = \begin{cases} 0 & \text{if } P_t < \Lambda_{i,t} \\ \frac{P_t - \Lambda_{i,t}}{\lambda^j_2} K_i & \text{if } \Lambda_{i,t} < P_t < \Lambda_{i,t} + \lambda^j_2 \\ K_i & \text{if } P_t > \Lambda_{i,t} + \lambda^j_2 \end{cases} \tag{5}$$

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

Plants cannot produce negative amounts of electricity[20], so for sufficiently low prices, $P_t < \Lambda_{i,t}$, plants do not generate anything. For prices above this "turn on" point, plants generate as a linear function of both price and capacity up until they reach their capacity constraint K_i. The capacity constraint physically limits output so that for $P_t > \Lambda_{i,t} + \lambda^j_2$ generation is perfectly inelastic at K_i.

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

$$\pi^j(\eta_t, K_i) = \begin{cases} 0 & \text{if } P_t \leq \Lambda_{i,t} \\ K_i \frac{(P_t - \Lambda_{i,t})^2}{2\lambda^j_2} & \text{if } \Lambda_{i,t} < P_t < \Lambda_{i,t} + \lambda^j_2 \\ K_i (P_t - \Lambda_{i,t} - \frac{\lambda^j_2}{2}) & \text{if } P_t > \Lambda_{i,t} + \lambda^j_2 \end{cases} \tag{6}$$

5.2.3 Wholesale Prices

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

$$\tilde{D}_t = D_t - Q^N_t - \sum_{i \in NT} q^{NT}_{i,t}(\eta_t, K_i) \tag{7}$$

[20] 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, 2024).

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

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

5.3 Investment in Capacity

5.3.1 Investment value function

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

$$V(K_i) = \mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi^j(\eta_t, K_i)] - \delta_1^{j,l} K_i - \delta_2^j K_i^2 - \nu_i K_i \tag{8}$$

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

$$K_i^* = \frac{\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, K_i^*)] - \delta_1^{j,l} - \nu_i}{2\delta_2^j} \tag{9}$$

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

5.3.2 State transitions

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

$$
\begin{aligned}
tmp_{l,t} =& f_{tmp,l}(month_t, v_t^{tmp}, u_{l,t}^{tmp,l}) && (10)\\
z_{l,t} =& f_{z,l}(tmp_{l,t}, month_t, v_t^z, u_{l,t}^{z,l}) && (11)\\
\omega_{l,t} =& f_{\omega,l}(month_t, v_t^\omega, u_{l,t}^{\omega,l}) && (12)\\
D_t =& f_D(month_t, \overline{tmp_t}, \overline{tmp_t^2}, \overline{z_t}, D_{t-1}, P_{t-1}, v_t^D) && (13)
\end{aligned}
$$

The over line notation denotes the market average of the state variable. Notice the resulting distributions of the environmental state variables in Equations 10-11 are location specific, seasonal, subject to an idiosyncratic shock $u_{l,t}$, and correlated across space through a common shock v_t. Drought is also correlated with local temperature, reflective of the natural hydrologic processes leading to drought (Vose et al., 2014). Additionally, while load is correlated with lagged prices, it is perfectly inelastic with respect to current prices P_t. This assumption stems from the structure of electricity markets where contracting between load serving entities and energy producers results in lagged pass through of prices, so that the end price consumers pay, and respond to, is an average of previous prices, P_{t-1}, and not the current spot market price itself, P_t.

Forming expectations over future prices in period $t = 0$ is complicated by the fact that prices are an equilibrium object, determined in part by each plant's capacity decision. For tractability of estimation, the model limits strategic investment behavior by assuming plants operate in an oblivious equilibrium, with each firm making their investment decisions based only on their own state variables (specifically location, technology and investment cost shock) and a long-run average future price, $\hat{P}$. This structure assumes that individual investment does not impact future prices. In combination with the laws of motion for the state variables, plants form expectations over future profit streams to solve for their optimal capacity investment with the modified version of Equation 9:

$$K_i^* = \frac{\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, K_i^*, \hat{P}_t)] - \delta_1^{j,l} - \nu_i}{2\delta_2^j} \tag{14}$$

6 Model Estimation

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

6.1 Spot Market Production Costs

I estimate the parameters governing the marginal cost functions from the firms' first order conditions. The firm first order condition returns ${q^*}_{i,t}^j$ as in Equation 5, which is replicated and slightly rearranged in Equation 15. This provides a structure to estimate the cost function parameters with regression analysis, given data on the plant level total amount generated $q_{i,t}^j$, capacity K_i, equilibrium market average wholesale price P_t, and environmental and market covariates.

$$\frac{q^{*j}_{i,t}}{K_i} = \begin{cases} 0 & \text{if } P_t < \Lambda_{i,t} \\ \frac{P_t - \Lambda_{i,t}}{\lambda_2^j} & \text{if } \Lambda_{i,t} < P_t < \Lambda_{i,t} + \lambda_2^j \\ 1 & \text{if } P_t > \Lambda_{i,t} + \lambda_2^j \end{cases} \tag{15}$$
$$\text{where } \Lambda_{i,t} = \lambda_1^j + \rho^j z_{l,t} + \gamma^j X_{i,t} + \phi_i + \varepsilon_{i,t}$$

I estimate Equation 15 with a tobit regression model, estimated via maximum likelihood. In absence of the capacity constraints, the firm's optimal $\frac{q^{*j}_{i,t}}{K_i}$ would equal $\frac{P_t - \Lambda_{i,t}}{\lambda_2^j}$. However, because of the capacity constraints the generation amount observed in the data $\frac{q^j_{i,t}}{K_i}$ is a censored version of the optimal generation choice, leading to the Tobit specification. Note that this specification is essentially identical to that used in the analyses of generation based on Equation 1.[21]

Similar to the discussion in Section 4, the identification of most of the cost function parameters stems from temporal variation. In particular, the cost parameters on drought are identified from linking deviations from normal hydrologic conditions with changes in plant level production. Identification of λ_1^j and λ_2^j is more complicated, since P_t is an equilibrium object, and therefore a function of $\varepsilon_{i,t}$. With aggregate shocks causing cross-sectional correlation in $\varepsilon_{i,t}$, estimates for λ_1^j and λ_2^j will be biased.[22]

I therefore instrument for P_t with total load D_t (linearly detrended to accommodate the one-time investment structure), the market average drought $\overline{z_{l,t}}$, and total generation from non-thermals $\sum_{i \in NT} q^{NT}_{i,t}(\eta_t, K_i)$. The first stage parameters are estimated concurrently within the Tobit maximum likelihood estimation. Demand is both a relevant instrument for price, reflected by the high F-statistics shown in Table 2, and exogenous since demand is short-run price inelastic (Bushnell, Mansur, and Saravia, 2008; Reguant, 2019). A risk to demand being a valid instrument is if the aggregate shock part of $\varepsilon_{i,t}$ is autocorrelated. As

[21] Two key differences between Equations 1 and 15 are that I define only two categories of drought and use the market average price instead of hub price to estimate Equation 15. I use the market average price to maintain consistency with the model set up.

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

shown in Equation 13, demand is long-run price elastic so that if the aggregate shock part of $\varepsilon_{i,t}$ is autocorrelated, the dependence of D_t on P_{t-1} results in correlation between D_t and $\varepsilon_{i,t}$. This channel of bias is likely quite weak though, since determination of demand is dominated by seasonality and temperature variation. Regressing D_t on month fixed effects alone results in an R^2 value of 0.8 (Appendix Table A5), leaving relatively little room for robust correlation with the aggregate shock. I also include the instrument of market average drought to capture the indirect effect of drought through changes in the market equilibrium documented in Section 4. Lastly, I include the instrument of total generation from non-thermals since this has no direct impact on thermal plant generation except through changing the wholesale price.

The estimated cost parameters are presented in Table 2. The first row shows the estimates of the cost curve curvature (λ_2^j) with respect to share of capacity used. Across all three technologies, marginal costs are increasing as plants produce closer to capacity. Using the full set of cost parameters to trace out the marginal cost curves for each plant type shows that high water use and low water use plants are consistently cheaper than dry cooled plants (Appendix Figure A12). This implies high water and low water use plants come online first, while the more expensive dry cooled plants operate as peaker plants - in line with anecdotal descriptions of these technologies.

The key parameters of interest, ρ_1^j and ρ_2^j, show that drought significantly increases costs only for high water use plants. For high water use plants, moderate to severe drought increases marginal production costs by \$11.51/MWh while extreme drought increases costs by \$26.30/MWh. Compared to an average wholesale price of \$24/MWh, these estimates reflect substantial increases in operating costs. The last two rows show the marginal cost parameter estimates for temperature. For both high and low water use plants, higher temperatures lead to statistically insignificant higher production costs, while dry cooled plants show a negative relationship over the range of sample temperatures.

Table 2: Cost Function Parameters

	High water use	Low water use	Dry
Capacity used: λ_2^j	248.4***	410.5***	333.9***
	(48.24)	(60.77)	(30.01)
Moderate-Severe: β_1^j	11.51***	-0.590	1.169
	(2.209)	(1.848)	(1.206)
Extreme: β_2^j	26.30***	0.196	2.943
	(3.643)	(3.144)	(2.110)
Temperature	32.30	12.14	-66.06***
	(28.64)	(16.40)	(9.104)
Temperature^2	-0.0539	-0.0202	0.119***
	(0.0493)	(0.0284)	(0.0158)
F-stat	206	1350	1837
Observations	1,960	8,963	11,197

Notes: Table presents parameter estimates for thermal firm cost functions. Parameters are estimated separately for each technology type. The estimate marginal cost at the average level of generation and the first stage F-statistic are shown at bottom. Standard errors are shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

6.2 State Transition Parameters

I estimate the parameters dictating the transition of state variables over time (Equations 10-13) offline using the available data for plants in ERCOT from 2000 through 2022.[23] For temperature, drought, and renewable capacity factors, I estimate the parameters using ordinary least squares with a location level panel. For quantity demanded I use ordinary least squares with market level time-series data.

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

[23]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.

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

6.3 Investment Costs

I use the plant first order condition from Equation 9 to estimate the investment cost parameters. Under Equation 9, the optimal level of new capacity investment is a linear function of expected future marginal profits, $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$, and an idiosyncratic investment cost shock, ν_i which is assumed to be exogenous to production shocks faced by the plant (ε_{it}). By Equation 6, profit each period is linear in K_i, so that in combination with independence of η_i and ε_{it}, $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$ is exogenous.

I first numerically solve for $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$ for each plant via simulation as described above. I then regress K_i, measured in the data as the plant level total capacity as of December 2022, on $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$ using technology specific subsets to capture heterogeneity in investment costs. Due to small samples, I combine high water and low water use plants, but include binary variables so that the linear term $\delta_1^{j,l}$ is type specific. Additionally, due to potentially thin samples within each climate division, I cluster divisions into three larger regions based on tercile of population density and estimate a unique linear investment cost for each larger region.

Two challenges for estimation arise from the censoring of investment at zero. First, the capacity measured in the data reflects a censored version of the true optimal capacity from Equation 9 since observed investment must be non-negative. I account for this by using

Table 3: Investment Cost Parameters

	Non-thermals	High water use	Low water use	Dry
Linear cost: $\delta_1^j/1{,}000$				
Low Pop. Density	704.84***	1,264.32***	3,422.00***	1,672.42***
	(41.28)	(60.50)	(107.21)	(145.59)
Mid Pop. Density	782.41***	1,192.29***	3,227.03***	1,600.20***
	(32.00)	(44.35)	(63.86)	(121.85)
High Pop. Density	957.28***	1,173.76***	3,176.88***	1,308.93***
	(75.45)	(46.50)	(70.47)	(30.35)
Quadratic cost: $\delta_2^j/1{,}000$	1.25***	0.04***	0.10***	1.21*
	(0.24)	(0.01)	(0.03)	(0.64)
Cost shock standard deviation: $\sigma_\nu^j/1{,}000$	466.15	100.93	273.18	402.93
Estimated cost per MW (millions)	.9500000000000001	1.23	3.32	1.48
EIA cost per MW (millions)	1.4	1.1-2.7	1.1-2.7	0.5

Note Table presents parameter estimates for investment cost parameters. Parameters are estimated separately for each technology type (column). Per MW investment costs at the median capacity investment observed in the data and reported (EIA) estimates of median (per MW) construction costs are shown at bottom. Standard errors are shown in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

a Tobit regression with censoring at zero. Second, the data set only contains observations of plants that have ever existed in ERCOT since 2000, and necessarily excludes hypothetical plants that were never constructed. This sample selection could bias the estimated cost parameters by ignoring a relevant subsample of plants. To address this, I incorporate a set of "never-constructed" plants into the sample, each with zero capacity and an expected marginal profit constructed following the same process as for the real plants.

The estimated investment cost parameters are shown in Table 3. Across all technologies marginal costs are convex in capacity size, reflected in the positive values for δ_2^j. I find that investment costs are lowest for non-thermal plants, with 1 MW of capacity costing $0.95 million. High water use and low water use thermals are more expensive, with low water use thermals being significantly more expensive than high water use, inline with the additional cooling infrastructure requirements. Additionally, using the location specific linear investment costs I find that building thermal plants is relatively cheaper in more population dense areas, while building non-thermals is relatively cheaper in less densely populated areas. This is reasonable given the land use requirements for the different technologies.

My estimated investment costs align relatively well compared to construction cost estimates from the EIA for approximately comparable plants, as shown in the last two lines of the table.[24] Additionally, my results are comparable to econometrically identified estimates from Gowrisankaran, Langer, and Reguant (2024), who estimate a 250 MW combined cycle natural gas (comparable to a high or low water use thermal) investment costs $692 million. My results scale to a total cost between $318 and $861 million, depending on cooling technology.

6.4 Model Fit

I find that the modeled spot market process produces market equilibrium prices that are on average similar to those observed in the data. To test the model fit of the spot market stage of the model, I simulate state space realizations (including persistent plant specific productivity shock draws) and solve for the equilibrium price. The results of this exercise are shown in column 2 of Table 4. Panel A of the table shows that capacity investment compared to the data are mechanically identical. With respect to prices, Panel B shows that the model predicts similar average prices to those in the data, though the model generally overestimates prices during non-drought periods and underestimates during drought. Additionally, as shown in Panel C, modeled prices are more volatile than prices in the data. The third column shows that when incorporating investment, the model over predicts investment in dry cooled plants and under predicts investment in high water use plants. However, these differences in investment lead to only a marginally worse fit with respect to prices.

7 Counterfactual Drought Scenarios

This section presents counterfactual analyses, simulating investment and production in ERCOT under alternative climate scenarios. The goal of this exercise is to understand 1) how does the grid investment respond to alternative climate futures, 2) what are the costs and benefits of this adaptation, and 3) to what extent does including correlated drought changes

[24]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 4: Model Fit

	Data	Data Capacity Simulated Market	Simulated Capacity Simulated Market
Panel A: Capacity Share			
Non-thermal	38.66	38.66	41.00
High Water	11.20	11.20	4.95
Low Water	37.17	37.17	35.52
Dry	12.97	12.97	18.53
Panel B: Average Price			
Average	23.82	24.90	25.40
Non-drought	20.59	24.00	24.36
Drought	30.28	27.14	27.95
Panel C: Price Standard Deviation			
Average	13.66	27.03	27.88
Non-drought	9.50	26.15	26.88
Drought	17.78	28.50	29.53

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

exacerbate effects beyond temperature change alone. For 1 and 2, I compare the counterfactual market equilibriums across two simulations, one without and one with endogenous investment. For 3, I compare the counterfactual equilibriums across climate simulations, one in which only the temperature distribution changes and one in which the joint distribution of temperature and drought changes.

To model future climate conditions I alter the distribution from which temperature is drawn by increasing the mean, using forecasts of future monthly average temperatures from two alternative emissions scenarios from the Coupled Model Intercomparison Project (CMIP6) to do so.[25] The first emissions scenario, SSP2-4.5, assumes low-to-moderate current emissions resulting in an increase in average temperature around 2.5°C. The second scenario, SSP5-8.5, assumes high emissions leading to an average temperature increase of 5°C.[26] For

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

[26] 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 (**government˙cmip6˙2023**).

the main analyses, these increases in mean temperature also result in increased frequency and severity of drought through the dependence of modeled drought on contemporaneous temperature. My modeled drought increases by 1.1 index points under the SSP2-4.5 scenario, and by 2.3 index points under the SSP5-8.5 scenario (Figure A13). These estimates of future drought conditions align closely with more rigorous estimates from the climate modeling literature, which predict increases in Texas drought between 0.5 and 1 index point for SSP2-4.5 and 1 and 1.5 index points for SSP5-8.5 (Zhao and Dai, 2022).[27] For comparative purposes, I also define a "baseline" climate scenario which defines the joint distribution of temperature and drought to match that observed in the analysis sample.

I use the following process to solve for the counterfactual equilibrium market outcomes. For each plant in the sample, I first solve for $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$ based on the relevant climate parameters. In simulations with endogenous investment, the $\hat{P}_t$ and η_t used to calculate $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$ depend on the counterfactual temperature and drought joint distribution.[28] In simulations without endogenous investment, the $\hat{P}_t$ and η_t used to calculate $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$ depend on the original joint distribution from the data. I then simulate optimal capacity investment following Equation 9. Lastly, I repeatedly simulate the spot market process to solve for the market variables of interest as a function of the simulated capacities and counterfactual state variables.

7.1 Changes in Investment

I first consider the change in generation mix across the alternative climate scenarios, shown in Table 5. I find that relative to baseline, investment in low water use plants increases significantly, doubling from 39% of total capacity to 60%. Non-thermals also show a modest increase. Both high water use and dry cooled plants see declines in investment, with high water plants seeing the largest relative decline (70%) and dry cooled plants seeing the larger level decrease. Looking across the two future counterfactuals, there is relatively little difference in the resultant generation mixes suggesting that adaptation responds non-linear to

[27]The predictions from Zhao and Dai (2022) measure drought using the PDSI index, which is closely related to the PHDI but not identical.

[28]Calculation of $\mathbb{E}[\sum_{t=1}^{T^j} \beta^t \pi'^j(\eta_t, \hat{P}_t, K_i^*)]$ ensuring rational expectations relies on repeating the iterative process outlined in Section 6.2 for every simulation.

climate change severity.

Table 5: Simulated Total Investment (MW)

	Baseline	SSP2-4.5	SSP5-8.5
Panel A: Capacity Share			
Non-thermal	52,461	57,584	57,635
	(37.84)	(31.22)	(31.44)
High Water	7,129	2,043	1,475
	(5.14)	(1.11)	(0.80)
Low Water	53,859	110,843	110,429
	(38.85)	(60.10)	(60.25)
Dry	25,174	13,955	13,750
	(18.16)	(7.57)	(7.50)
Panel B: Total Investment			
Total Capacity	138,623	184,424	183,289
Total Cost ($ Billions)	291.57	466.50	464.09
Cost per MW ($ Millions)	2.10	2.53	2.53

Notes: Table presents simulated capacity investment under baseline and counterfactual climate conditions. Panel A shows capacity investment in each technology type, both as the MW amount as well as the percent of total investment. Panel B shows the total capacity investment in the market (in MW) and the associated cost in billions of dollars.

In aggregate, the results show that total capacity investment increases under the alternative climate futures. While the increase in investment mechanically leads to a higher investment cost, the change in generation mix also contributes to a higher per MW cost. In the baseline scenario, the average cost is $2.1 million/MW, but in the climate change scenarios the increase in expensive, low water use technology pushes the average cost to around $2.5 million/MW. In total, preemptive adaptation leads to shifts in the equilibrium generation mix which require an increase in total investment of about $174 billion relative to the baseline scenario.

In addition to switching technologies, firms may change the location of investment. Plants individually were not allowed to choose an investment location in the model, however in aggregate if firms increase entry into certain locations or disproportionately withhold investment then that would drive market level shifts across space. Mapping the counterfactual investment across technology types shows that migration of investment is minimal (Figure 6). Instead, it appears that changes in capacity within technology type occur relatively uniformly across space, with all climate division reducing the share of capacity belonging to dry and high water use plants and increasing the share of capacity belonging to low water use relative to the baseline scenario.

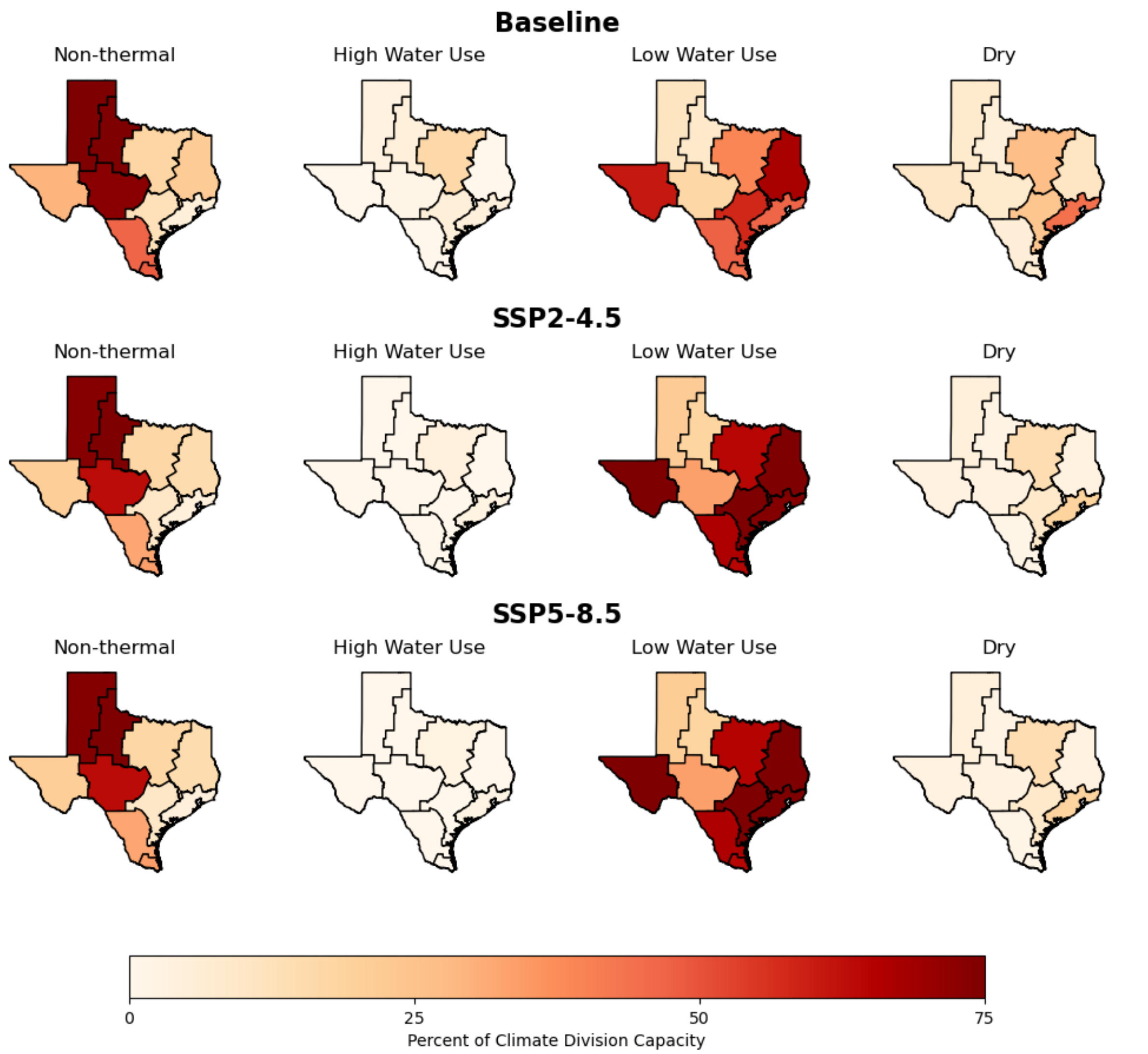
7.2 Changes in Market Outcomes

I next examine the counterfactual market outcomes of wholesale energy prices, demand, and firms revenues. To quantify the benefits and costs of adaptation associated with each of these outcomes, I run the three counterfactual scenarios both with and without adaptation of the technology mix. The results under the exogenous technology mix can be interpreted as similar to existing work by extrapolating from historic effect estimates, but with the model framework incorporating market dynamics in a more rigorous way.

I first consider the market without adaptation, finding significant increases in the average wholesale energy prices with warmer climate futures (Panel A of Table 6). The average price per MWh doubles from the baseline average of $25.41 to $49.97 under the SSP2-4.5 scenario and more than triples under the more severe SSP5-8.5 scenario. This average price impact is due to both increased demand from higher temperatures (Panel B), as well as realizing the more expensive drought state more often. Breaking the price increase apart for drought and non-drought periods suggests there is some degree of compounding effect between temperature and drought, with the price increasing across climate scenarios more for drought periods than non-drought periods. It appears that this compounding is potentially a side effect of the increased demand. Panel B shows that without adaptation, all thermal plants increase average production to meet the higher demand, leaving less flexibility in the system to respond to drought shocks and requiring high water use plants to continue operating to meet demand even with higher production costs during drought. This increase in production across the board in combination with higher prices leads to substantially higher revenues for all firms.

Turning to the role of adaptation, I find that the endogenous shift in generation technologies entirely eliminates any increases in wholesale prices relative to baseline levels. This

Figure 6: Spatial Variation in Counterfactual Investment



Notes: Figure maps the share of capacity within a given climate division belonging to each technology type across the three climate scenarios.

Table 6: Simulated Equilibrium Market Outcomes

		Without Adaptation		With Adaptation	
	Baseline	SSP2-4.5	SSP2-8.5	SSP2-4.5	SSP5-8.5
Panel A: Average Price					
Average	25.41	49.97	84.17	24.88	25.39
Non-drought	24.36	46.38	75.62	22.31	22.77
Drought	27.95	55.11	91.86	27.12	27.67
Panel B: Average Quantity (MWh)					
Demand	30,991,077	34,601,080	39,262,113	43,584,832	43,548,725
Non-thermal Generation	34,429	34,429	34,429	35,739	35,748
High Water Generation	85,410	119,948	169,529	68,889	65,372
Low Water Generation	240,215	270,197	310,012	288,641	288,937
Dry Generation	20,539	23,176	27,802	14,535	14,576
Panel C: Firm Revenues ($ Thousands)					
Non-thermal	710	1,504	2,636	760	772
High Water Use	3,596	10,003	22,463	3,242	3,172
Low Water Use	7,255	16,782	32,535	8,928	9,096
Dry	639	1,488	3,094	440	451

Note Table presents simulated equilibrium prices on average, during non-drought periods, and during drought periods. The first set of columns denotes the simulation using the historic drought distribution while the second and third columns use the projected drought distributions under the Low-to-Moderate and High scenarios. Columns denoted Exog are estimated using the simulated technology mix under Baseline conditions (Column 1 of Table 5). Columns denoted Endog are estimated using the simulated technology mix under the respective climate scenario.

occurs even though demand significantly increases (40% relative to baseline), and increases more than in the scenarios without adaptation. Scaling average quantity demanded by average price, the results indicate that adaptation of the generation mix reduces total monthly expenditure on electricity by \$644 million under the SSP2-4.5 scenario and\$2.2 billion under the SSP5-8.5 scenario relative to no adaptation.

Additionally, the relatively lower energy prices reduce firm revenues to levels only slightly higher than those in the baseline scenario. In line with the equilibrium investment, revenues actually decline for the high water use and dry cooled plants relative to baseline since these plants on average produce relatively less. Low water use plants are the main "winners" under the alternative climate futures as they increase plant level generation (up to 20%) increasing their total revenues. Note though that the increasing production costs as plants approach capacity make the profit impact somewhat ambiguous. Analysis with respect to profits are forthcoming.

7.3 Role of Drought

For the last exercise, I examine the importance of accounting for the correlation of drought and temperature in estimating climate damages. To do this, I repeat the main analyses, but shut down the correlation between drought and temperature. This results in mean temperature increasing in the climate counterfactuals but the drought distribution remaining identical to the baseline distribution. The results from these simulations are compared to the main results in forthcoming work.

8 Conclusion

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

This paper examines the potential impact climate change may have on electricity markets. I first look at how drought shocks have previously impacted equilibrium generation and prices, and find that local drought shifts generation away from high water use plants towards dry cooled plants and leads to significant price increases. I then forecast what the equilibrium mix of generating technologies would look like under alternative climate futures, and explore how equilibrium market outcomes subsequently change. I find that in line with the reduced form analyses, investment shifts away from high water use plants and towards low water use thermal plants. Additionally, I find that this costly investment mitigates increases in wholesale energy prices that would otherwise occur. Back-of-the-envelop calculations place the net benefit of endogenous adaptation over 50 years between \$212 billion and \$1.1 trillion (depending on climate future) due to the reduction in wholesale energy prices alone. Extrapolating from existing literature would also suggest that the reductions in electricity prices would lead to other welfare benefits, through increased purchasing power and reductions in temperature-related mortality (**ppz14**; **cjo24**).

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 A1, 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 environmental 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 environmental shocks. This is an interesting area for policy, since is is ex ante unclear how precise firms beliefs are over future environmental conditions, and providing information could be a cheap and effective solution to facilitate adaptation. Lastly, the world of electricity generation is rapidly changing with new technologies and a proliferation of energy storage. While increased storage will likely help mitigate risk from climate change, an important caveat to note is that currently 96% of energy storage capacity is through pumped-storage power plants which are entirely powered by water. The effect on markets from climate change through these storage sources is another area in need of further research.

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Appendices

A Background Supplement

A.1 Details on ERCOT Market

The market in ERCOT is an aggregation of three separate, sequential markets. In the first market, the bilateral forward market, generating firms sell electricity directly to utilities under forward contracts, well in advance of the realized load. The majority of transactions in the whole sale market occur in the forward market. Generating firms then sell electricity to ERCOT through a bidding process in the day ahead market, which occurs one day before load is realized at 15 minute intervals. ERCOT purchases electricity so that the sum of generation in the day ahead market and the bilateral forward market equals the expected load at lowest cost. Lastly, firms again sell to ERCOT through a bidding process in the real-time market, which occurs every five minutes. ERCOT purchases electricity so that the sum of generation in the real-time market, the day ahead market, and the bilateral forward market equals the realized load at lowest cost. Because firms have the opportunity to operate in all three markets, prices across the three markets are highly correlated (**ercot˙2022**).

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

A.2 Details on Electricity Generation and Cooling

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

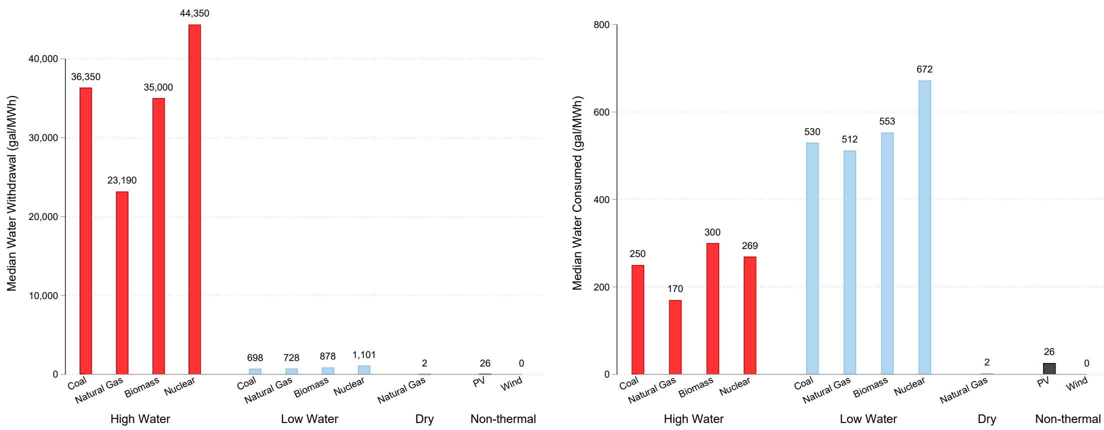
While many generators use steam as the prime mover, the system used to cool the prime mover after generation is actually the thirstiest part of the process. Cooling systems can be categorized into three general groups: once-through, recirculating, and dry. Once-through cooling systems (in this paper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

Besides determining the water needs of the generation process, the cooling system is important since it can impact overall thermal efficiency. From the Rankin cycle, having a larger change in temperature of the prime mover over the generation process leads to higher thermal efficiency. Because once-through systems are continually using new water they are better able to cool the prime mover back to lower temperatures after generation, resulting in a larger change in temperature over the generation process. In contrast, recirculating systems re-use water so that as it heats up it is more difficult to cool the prime mover to lower temperatures, resulting in a smaller change in temperature over the generation process. Similarly, dry cooled systems are less efficient at reducing the temperature of the prime mover. These differences in cooling result in meaningful differences in thermal efficiency of plants (**world˙nuke**; **epri**).

It is relevant to note that water withdrawn does not equate to water consumed.

Once-through cooled systems withdraw large volumes of water but return the majority of that water to the source. In contrast recirculating systems end up consuming almost all of the water withdrawn (see Figure A1). While consideration of consumption is important for water management and downstream users, it is beyond the scope of this paper.

Figure A1: Water Use by Technology



Notes: Figure plots the median volume of water withdrawn on the left and water consumed on the right, per MWh of electricity produced. Technologies are disaggregated along the x-axis, first by cooling and then by fuel type. Values are collected from **m11**.

B Data Supplement

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

B.1 Plant Characteristics

Capacity, dates, and location I start with data from the US Energy Information Administration (EIA) to identify power plants in the US. Using the EIA-860 forms which collect generator-level data for plants with at least 1MW of capacity, I compile a roster of all operating and retired generators in the US since 2001. I consider only power plants in the contiguous US. Each generator observation contains information on the generator's location, capacity, year and month of first operation and retirement, and a unique id for the power plant where the generator is located. I expand this roster into a monthly panel of generators. This is then aggregated into a panel of power plants containing information on plant operating/retirement dates and capacity. I define the date the plant is first operating as the earliest observed operating time of a generator at the plant. I define plant retirement similarly as the latest retirement of a generator, if all generators are retired. I then define plant level capacity each month as the sum of capacities of generators that are operating during that month.[29]

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

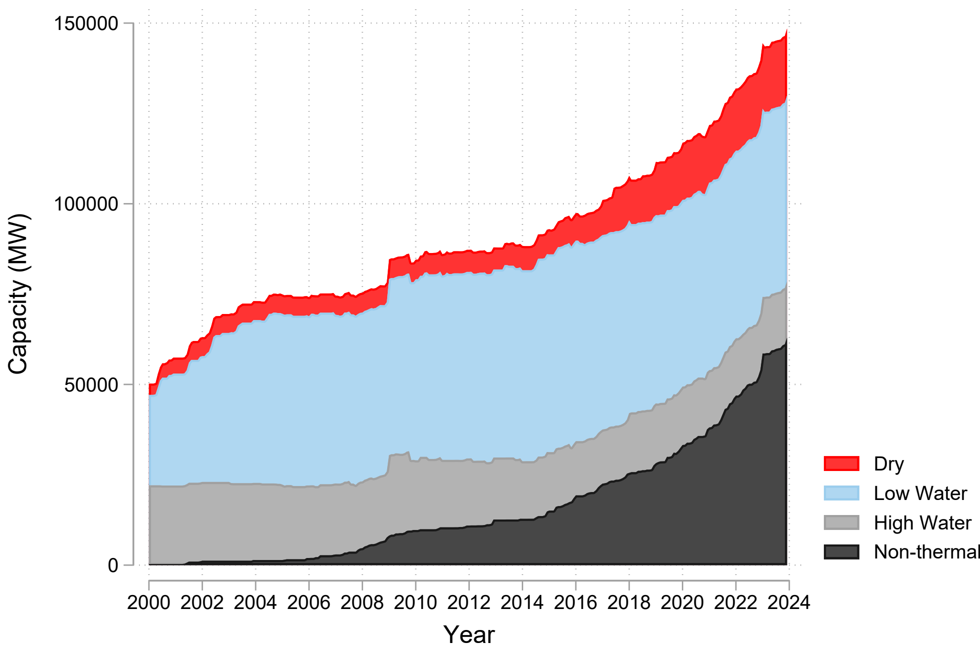
I define thermal plants as those that primarily use coal, natural gas, or petroleum for fuel. I omit nuclear and solar thermal generators from the thermal category, even though

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

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

Cooling I use the EIA-860, Schedule 6 form to identify the type of cooling used by plants: once through, recirculating, dry/hybrid, multiple. There are several caveats with this data however. First, only plants with over 100MW of capacity are required to fill out the form, though there is both non-compliance from some large plants and compliance from some smaller plants. Given the compliance rate is likely unrelated to drought conditions, this is not a threat to the internal validity of the analyses. Second, only plants with cooling systems are included. Since combustion turbines do not require cooling systems, plants with only combustion turbines would not appear in the data. As such I assume that all plants that are identified as primarily using combustion as the prime mover but are missing cooling information are dry cooled. Third, similar to fuel and prime mover types, a single plant may house multiple generators linked to multiple, different cooling systems. I identify the plant’s main cooling system type as follows. If a plant only has one type of cooling system observed as operational it is assigned that type of cooling system. Of the plants with cooling system data, this covers 81%. If a plant is observed as having multiple types of cooling systems observed as operational at any point (eg. switching technologies over time or being dual equipped) then it is assigned the type “multiple”. This accounts for 11% of the sample of plants with cooling data. Lastly, I repeat the process for plants that are associated with only retired cooling systems - those that only have one type are assigned that type (7%) while those with multiple are assigned to the “multiple” type group. The last concern is that the data is only available since 2009, though some plants that retired pre-2009 are still included. Since having multiple cooling types is relatively rare, I assume that plants do not switch technologies and assign plants their post-2009 cooling type as outlined above for all periods of the main analysis sample. The resulting distribution of cooling technologies over time is shown in Figure A2.

Figure A2: Technology Mix Over Time



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

US power plant characteristics I estimate identical descriptive statistics for the set of all US power plants for comparative purposes with the ERCOT subsample. These are shown in Table A1.

B.2 Market Data

Generation I use the EIA-923 form to identify the monthly plant level amount of energy generated. Monthly plant generation data is available from 2001 to 2023 at the plant-fuel-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.

Table A1: US Power Plant Characteristics

	Non-thermal	High Water	Low Water	Dry
Panel A: Aggregate Statistics				
Number of plants	7,592	295	521	3,054
Percent of total capacity	21	16	38	25
	(0.44)	(0.25)	(0.23)	(0.06)
Percent of total generation	22	13	54	11
	(4.55)	(1.03)	(3.32)	(1.46)
Panel B: Plant Statistics				
Operating year	2016.45	1958.81	1987.77	1991.92
	(5.89)	(11.90)	(20.60)	(22.22)
Age at retirement	18.56	59.20	43.42	30.02
	(10.36)	(11.12)	(15.18)	(20.56)
Mean capacity (MW)	30.90	589.74	797.17	88.38
	(71.49)	(753.98)	(710.71)	(226.97)
Mean generation (GWh)	7.80	144.29	274.79	11.91
	(19.01)	(224.21)	(248.15)	(55.75)
Water withdrawn (gal/MWh)	20.71	33671.65	610.48	2.00
	(10.47)	(7221.95)	(399.27)	
Water consumed (gal/MWh)	20.71	233.45	431.63	2.00
	(10.47)	(43.31)	(261.05)	
Capacity factor (%)	17.36	23.82	42.75	18.37
	(12.83)	(28.00)	(28.67)	(28.86)

Notes: Table presents descriptive statistics for US power plants that were operational at any point since 2000. Data is from January to December 2022. Standard deviations, shown in parentheses, are taken over both plants and time. Plant level water withdrawn and consumption are estimated based on fuel type, prime mover, and cooling system (**m11**).

Therefore, I assume that plants that are operational but missing generation data have zero generation and create an indicator for the plant being mothballed.

Prices and demand I use publicly available data from ERCOT for monthly measures of load and market clearing prices. For load, I sum the available hourly load data to get ERCOT wide total load (measured in MWh) for each month in my sample from 2002 to 2023. Market clearing prices (both DAM and RTM) are available in 15 minute intervals at both the hub level and the ERCOT wide average since 2010. I aggregate prices to the monthly level using a simple average of the 15 minute prices at both the hub and ERCOT wide level to measure the average wholesale market price. I also exploit the detailed nature of the price data to construct peak and non-peak prices at the hub and ERCOT level, defining peak prices as the average price from 1pm to 7pm and non-peak as the average from 7pm to 1pm.

I combine the power plant data with the ERCOT market data using the plant coordinates to map each plant to its respective ERCOT hub.

B.3 Drought Data

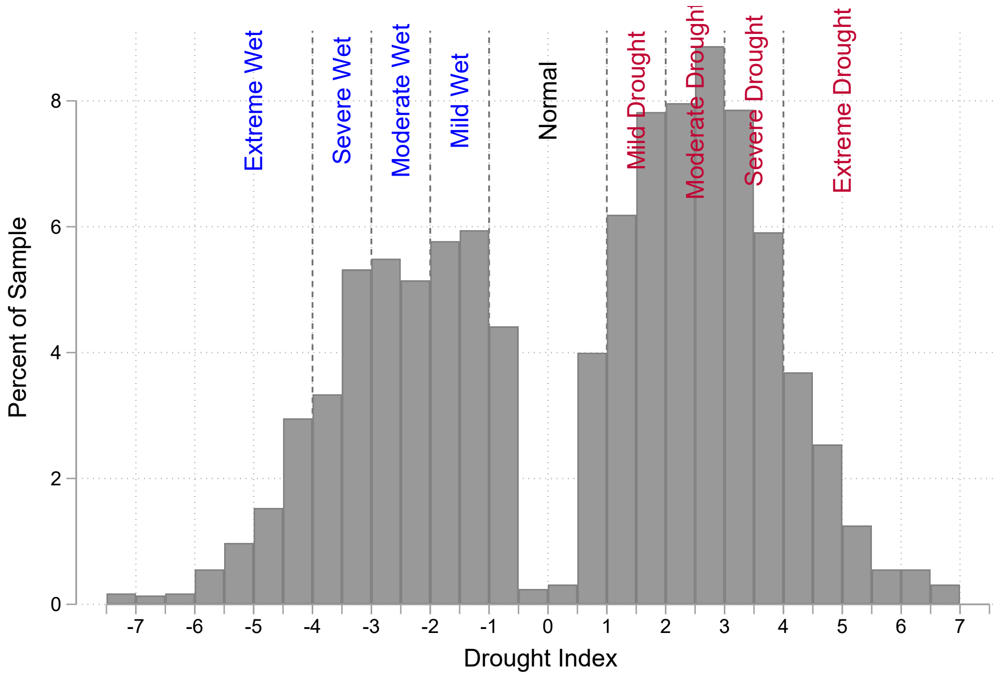
I measure drought in this analysis with the Palmer Hydrologic Drought Index (PHDI). This index measure uses a long range of historic data on monthly precipitation, temperature, soil moisture storage and a water balance model to classify hydrologic drought, such as changes in reservoir levels or stream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

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

B.4 Other Data Sources

I link the power plants in my sample to several other environmental and market variables. First, I use the coordinates of plants to link them to local environmental characteristics such

Figure A3: Histogram of PHDI Over Sample



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

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.

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.

C Drought and Production Supplementary Analyses

I addition to the main analyses, I also examine several alternative specifications, the results of which are presented here.

C.1 Analysis Summaries

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

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

USE PDSI and PRECIPITATION

I also examine the effect of drought duration, measured as continuous months in at least moderate drought (per the PHDI). I find that a one month increase in either local or non-local drought duration has negligible impacts on production quantities (Tables A2 and A3). However, Table A4 shows small but statistically significant increases in prices of around 1%. The 75th percentile of drought duration in the data is about 13 months, leading to an economically meaningful price increase for long droughts.

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

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

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

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

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

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

C.2 Tables

Table A2: 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	0.002***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,269	9,022	14,458	24,303

Notes: 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 A3: 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	-0.000	-0.000	0.004	0.000
	(0.001)	(0.000)	(0.003)	(0.000)
Observations	2,269	9,022	14,458	24,271

Notes: Table presents marginal effect estimates for the impact of local and non-local drought duration (in months) on the probability a plant is generating. 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 A4: Drought Duration Effect on Prices

	(1) Avgerage	(2) Non-peak	(3) Peak
Local drought	0.007***	0.012***	0.002***
	(0.001)	(0.002)	(0.001)
Non-local drought	0.007***	0.010***	0.004***
	(0.001)	(0.002)	(0.001)
Observations	51,677	36,205	16,565

Notes: 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.

C.3 Figures

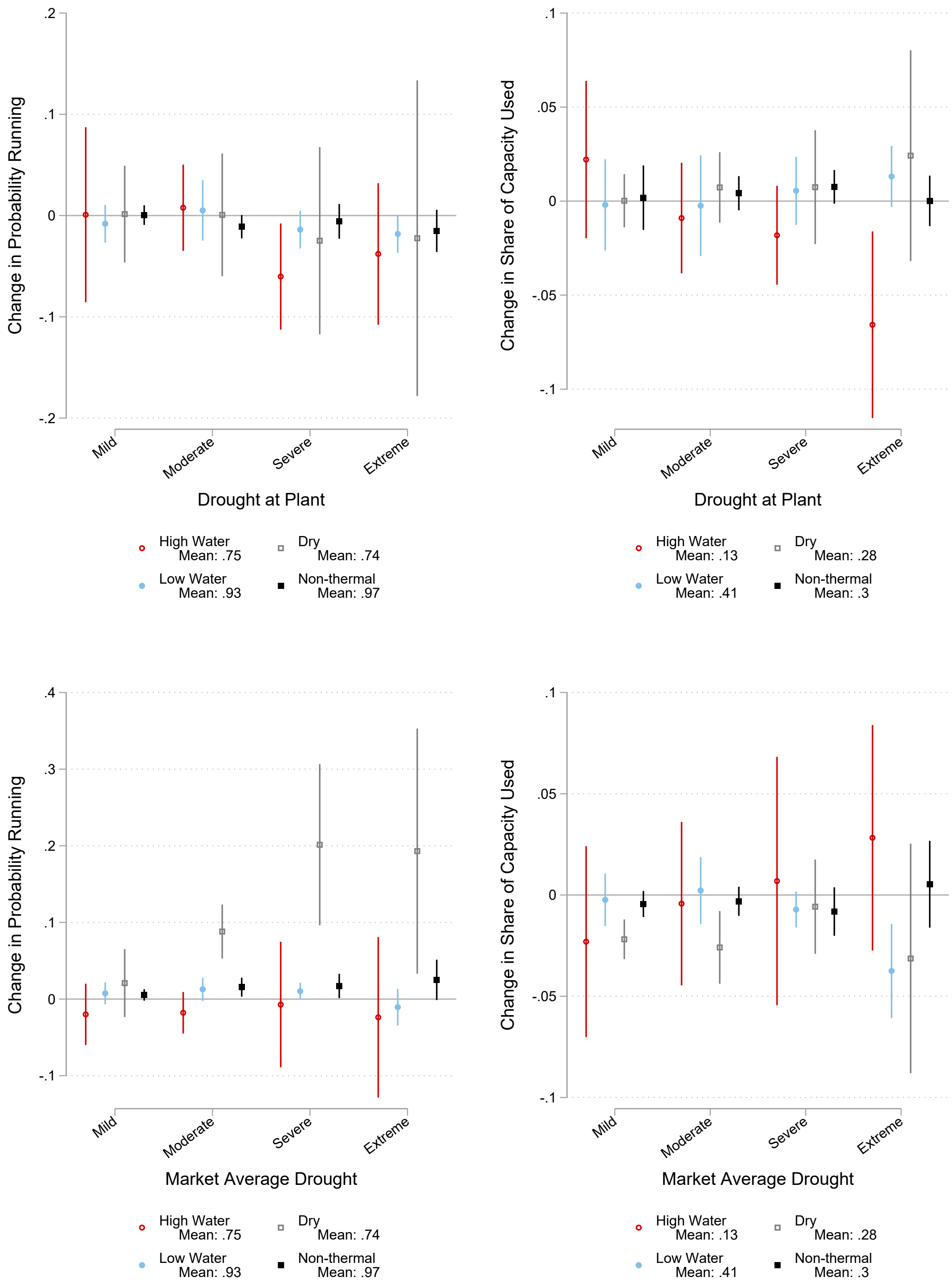
D Model Supplement

Table A5: Seasonality of State Variables

	Month and Location	Full
Temperature	0.964	0.996
Drought	0.024	0.071
Non-thermal Productivity	0.452	0.772
Detrended Demand	0.801	0.954

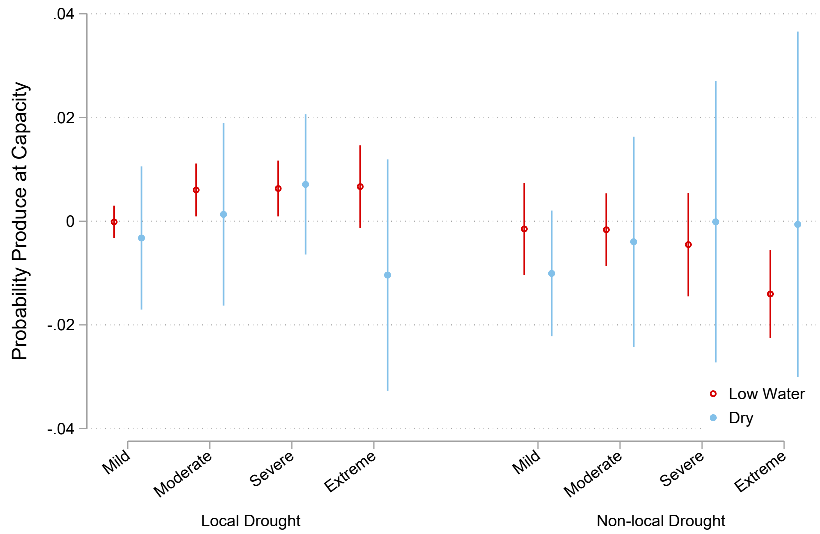
Notes: Table presents R^2 estimates from linear regressions using the variable shown on the left as the outcome variable. The first column includes month-of-year dummies interacted with climate division dummies for the first three rows. For detrended demand, the first column includes only month dummies. The second column reflects the specifications denoted in Equations 10-13.

Figure A4: Linear Probability Model Effect of Drought



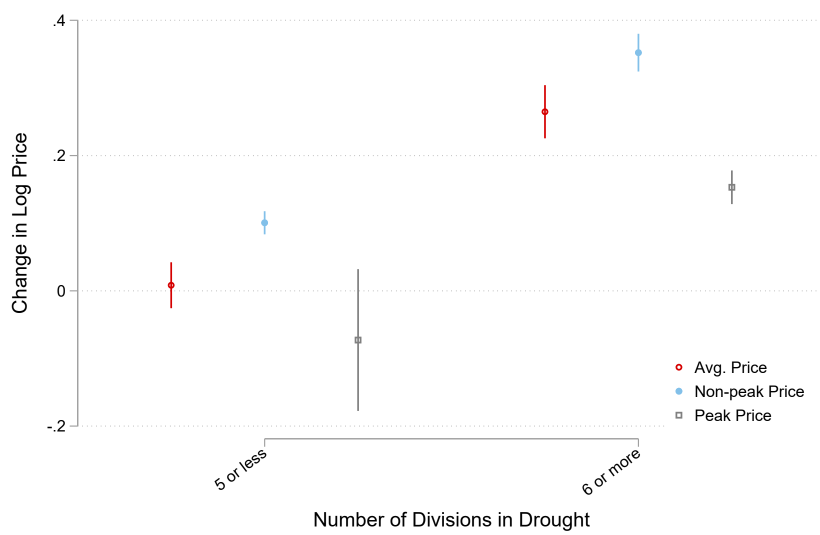
Notes: Figure plots effect estimates from a linear probability model for the impact of local and non-local drought on the share of capacity used and the probability a plant is running. The analyses are run separately for each of the four technology groups shown in the legend. Non-drought conditions are 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 A5: Drought Effect on Probability Plant is Capacity Constrained



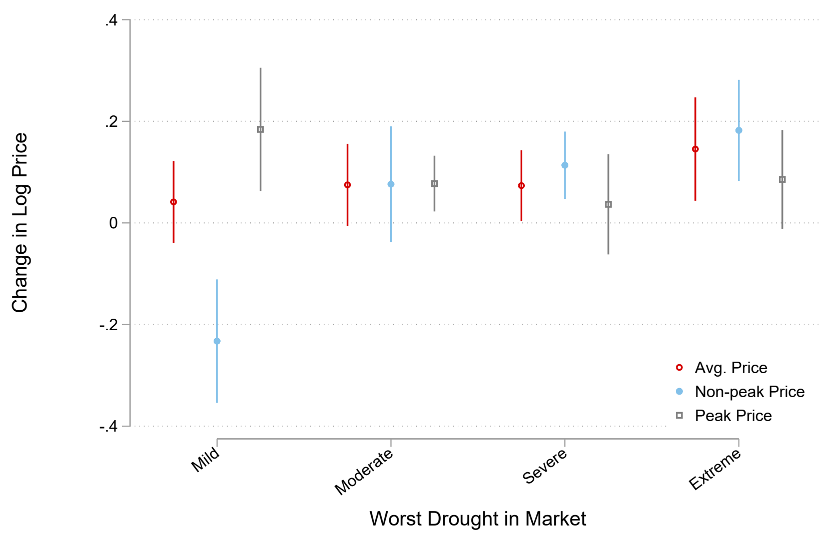
Notes: Figure plots marginal effect estimates for the impact of local and non-local drought on the probability a plant is producing at capacity. The analyses are run separately for each of the four technology groups shown in the legend. Non-drought conditions are the omitted category for both local and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

Figure A6: Number of Division in Drought Effect on Prices



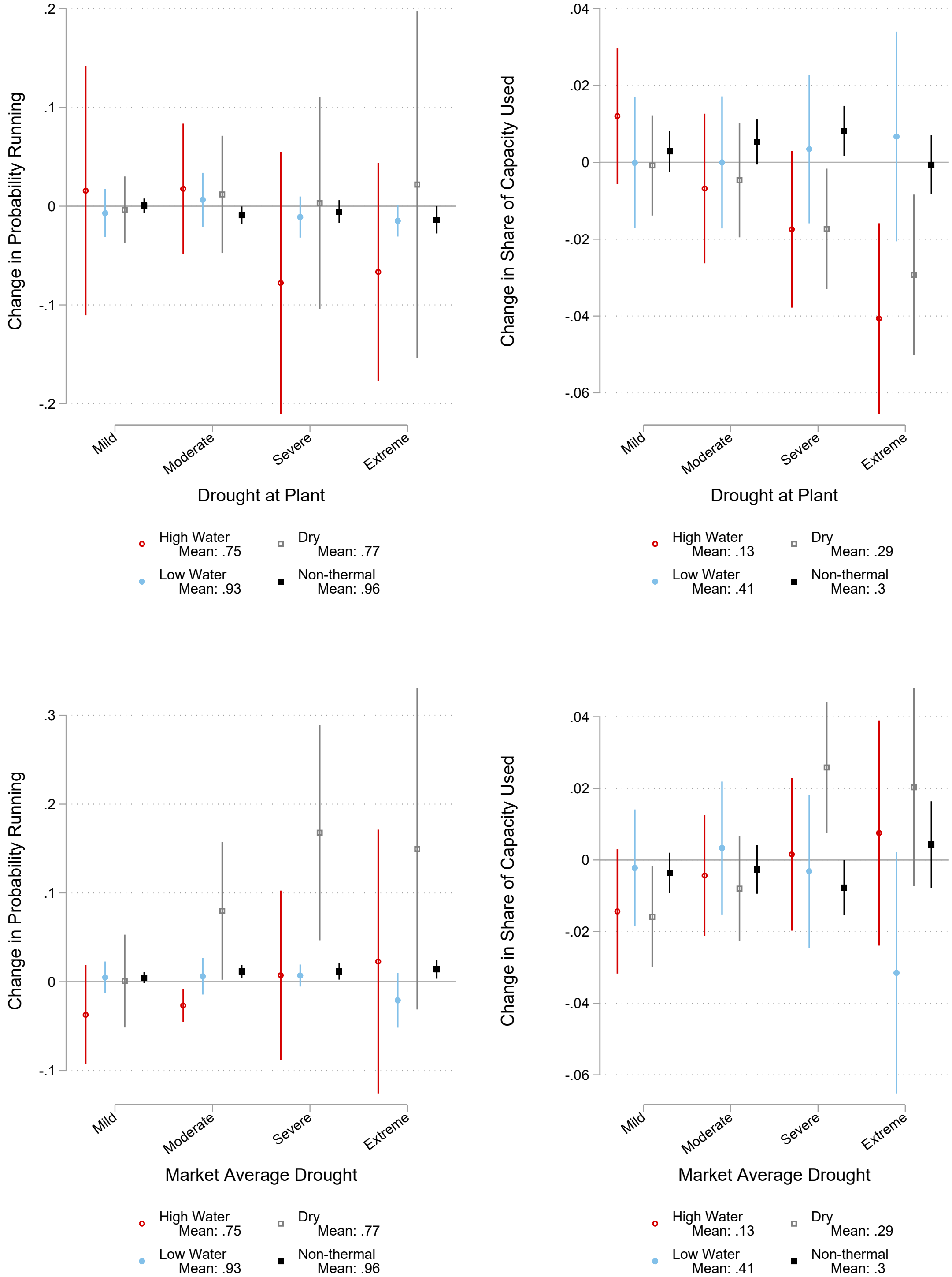
Notes: Figure plots coefficient estimates for the impact of the number of climate divisions experiencing at least severe drought on wholesale prices. The analysis is run separately for each of the three prices shown in the legend. Zero climate divisions in severe drought is the omitted category. Standard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

Figure A7: Worst Drought in Market Effect on Prices



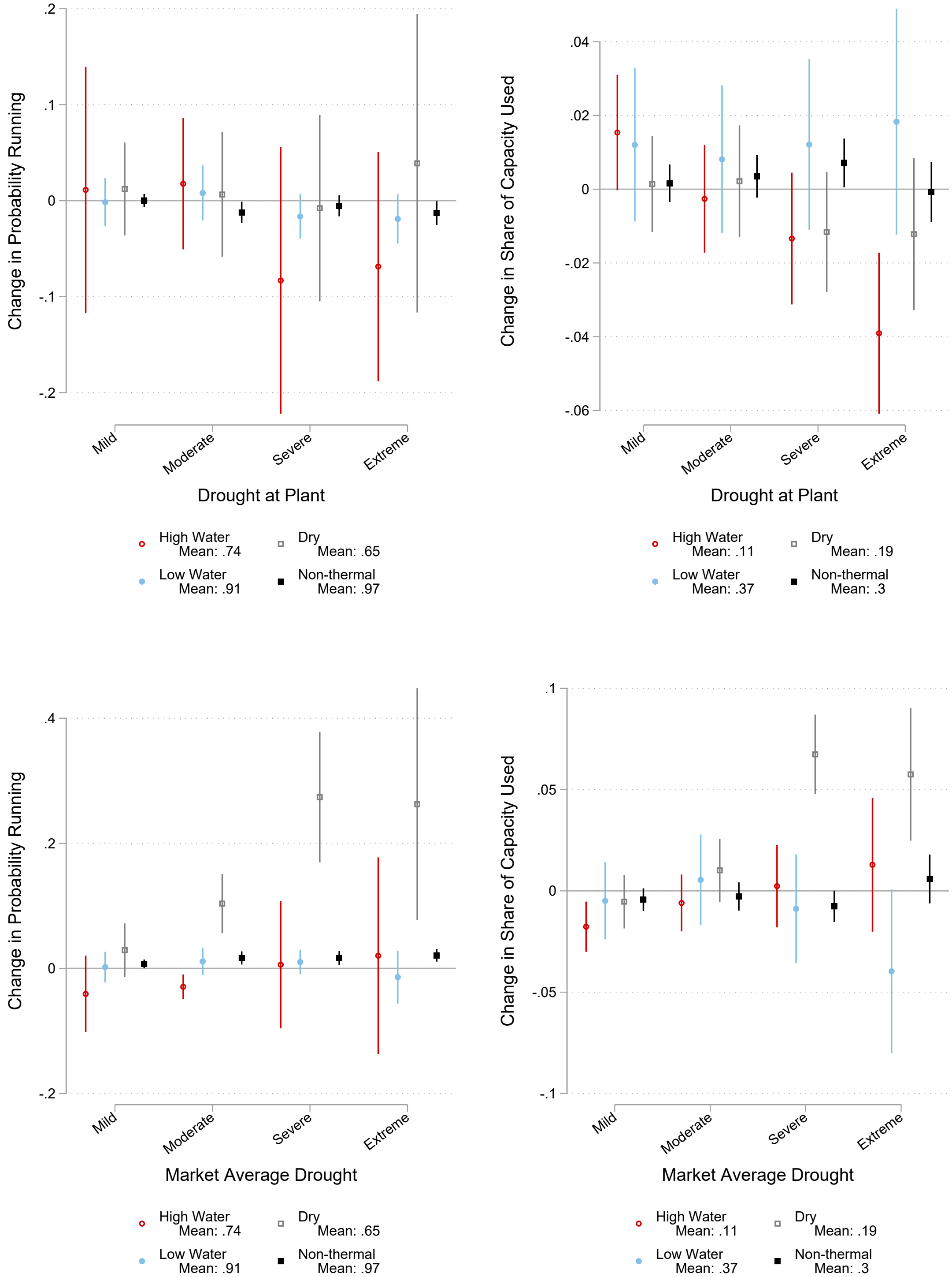
Notes: Figure plots coefficient estimates for the impact of the worst drought in the market on wholesale prices. The analysis is run separately for each of the three prices shown in the legend. Non-drought conditions are the omitted category. Standard errors are clustered at the climate division level. 95% confidence intervals are denoted by the vertical bars.

Figure A8: Production Response Including Non-Utility Plants



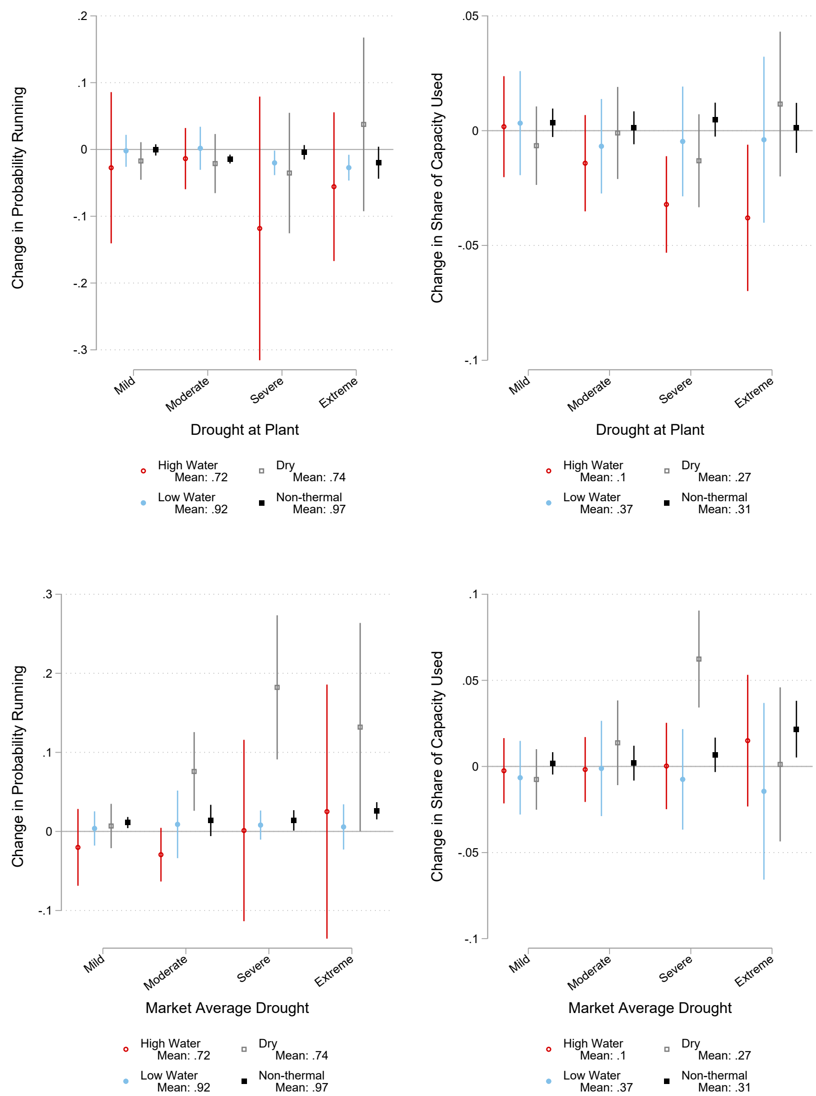
Notes: Figure plots marginal effect estimates for the impact of local and non-local drought on the share of capacity used and the probability a plant is running, for ERCOT plants including those not owned by a utility. The analyses are run separately for each of the four technology groups shown in the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

Figure A9: Production Response Omitting Cogeneration Plants



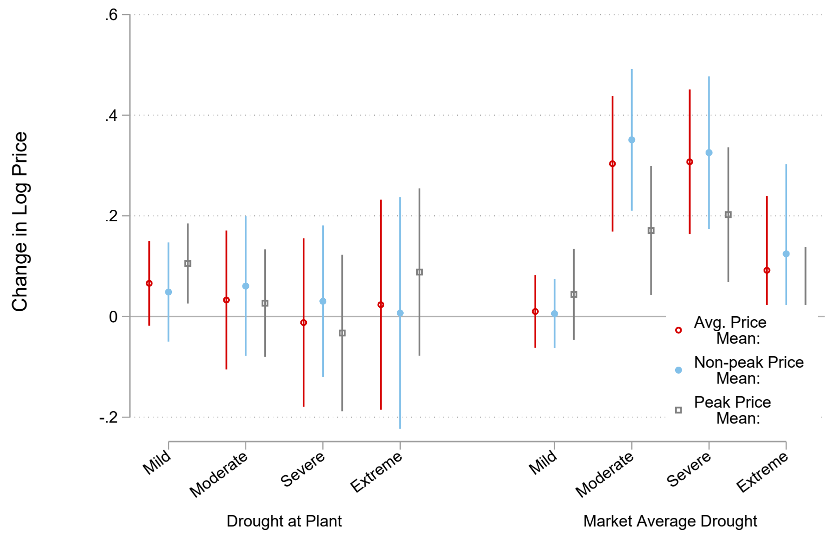
Notes: Figure plots marginal effect estimates for the impact of local and non-local drought on the share of capacity used and the probability a plant is running, for the subset of plants that are not combined heat and power plants. The analyses are run separately for each of the four technology groups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

Figure A10: Production Response During Non-Summer Months



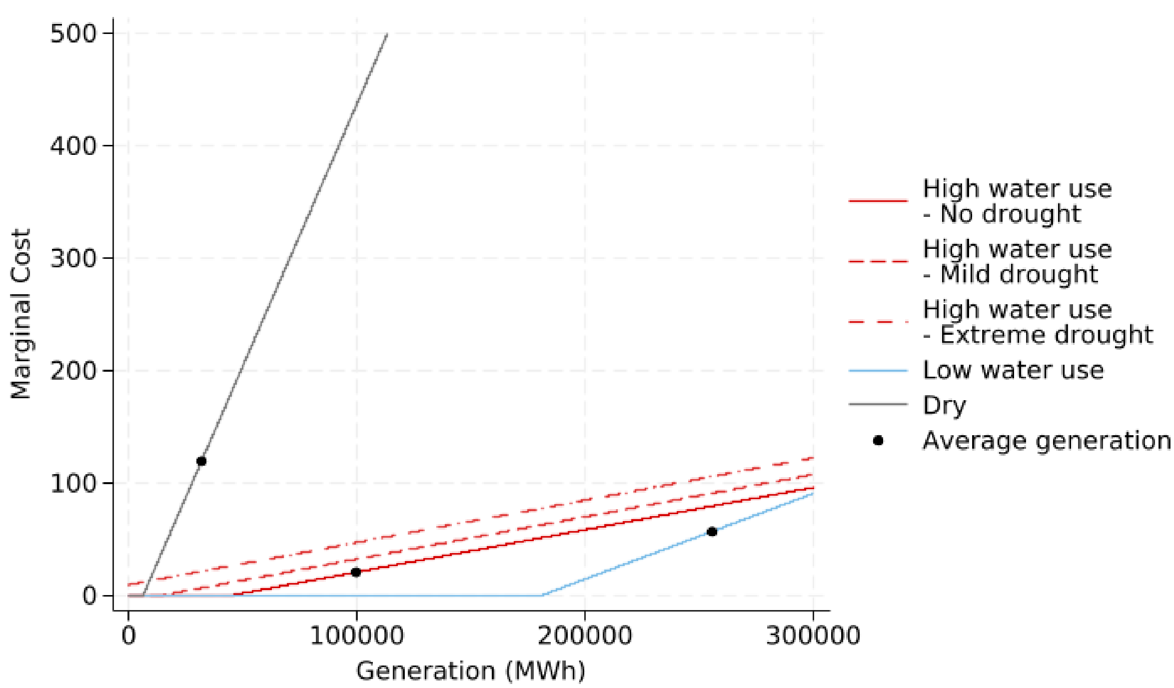
Notes: Figure plots marginal effect estimates for the impact of local and non-local drought on the share of capacity used and the probability a plant is running, for the subset of observations not occuring June through September. The analyses are run separately for each of the four technology groups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

Figure A11: Drought Effect on Non-Summer Wholesale Prices



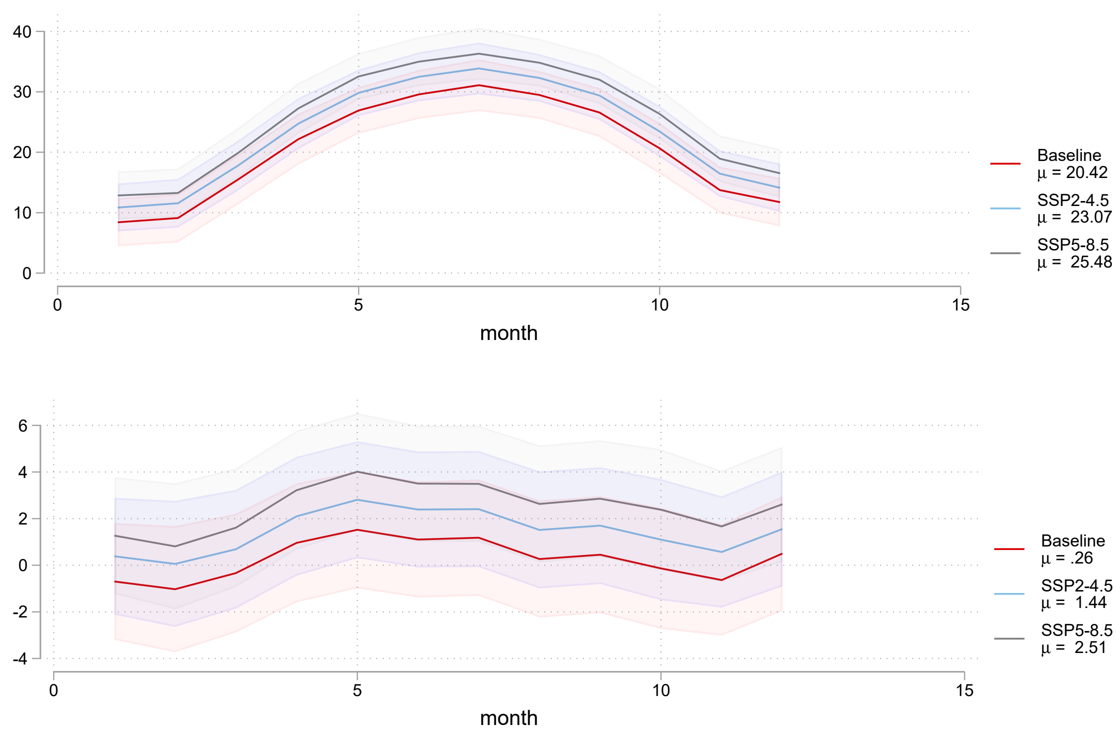
Notes: Figure plots coefficient estimates for the impact of local and non-local drought on wholesale prices in non-summer months. The analysis is run separately for each of the three prices shown in the legend. Non-drought conditions are the omitted category for both local and non-local drought. Standard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

Figure A12: Estimated Marginal Costs Curves



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

Figure A13: Simulated Climate Variable Trends



Notes: Figure plots simulated temperature and drought each month under the alternative climate scenarios. The solid line reflects the average while the shaded region denotes 1.96 standard deviations on either side.