

Infrastructure as Market Design: Location and Technology Choice on the Electric Grid*

Drew Van Kuiken

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Abstract

Economists have long recognized that infrastructure is important for welfare, but figuring out the marginal benefit of infrastructure is difficult. In this paper, I study how infrastructure shifts the equilibrium level, location, and technological composition of entry. My setting is the Texas electric grid, where transmission infrastructure is scarce and production varies by location and technology. I solve a dynamic entry game for renewable generators, capturing spatial and technological entry margins. Embedded within my entry game is a novel, physically realistic model of electricity dispatch, where electricity flows and prices are endogenous. The model is estimated using data from 2018-2024 with generation, transmission capacity, and demand information. I show that infrastructure provision policies distort entry locations and technology choices when generators and grid operators do not jointly solve for entry and infrastructure provision. I then consider counterfactual transmission provision policies. I find that entrants paying for their own upgrades, a policy commonly used throughout the U.S., reduces welfare by \$2.7 billion relative to Texas' baseline policy over the 2018-2024 period. I then implement a market for new transmission and find that it delivers similar welfare to the baseline policy while locating generators in better locations. My results suggest that entry in networks is distorted spatially and technologically, but policy that coordinates entry and infrastructure provision can eliminate that distortion.

*I am grateful to Jon Williams, Andy Yates, Gary Biglaiser, Marco Duarte, and Valentin Verdier for their help. I thank seminar and conference participants for helpful comments on this paper. Department of Economics, University of North Carolina at Chapel Hill, drew.van.kuiken@unc.edu.

Economists have long recognized that infrastructure is important for welfare, but figuring out the marginal benefit of infrastructure is difficult (Fernald, 1999; Duranton and Turner, 2011; Brancaccio et al., 2024). One potential reason: infrastructure availability shifts firm entry decisions. Prior literature suggests that the spatial allocation of firms depends on transport costs (e.g., Krugman, 1991; Desmet and Rossi-Hansberg, 2014) and rival firm positioning (e.g., Seim, 2006; Jia, 2008). This paper begins by observing that if benefits to infrastructure vary by firm, shifting infrastructure availability will change the equilibrium level and location of entry. Thus welfare changes depend on how infrastructure shifts the composition of firm entry, particularly when firms differ in their productivity, costs, or consumers they serve.

In this paper, I study how infrastructure policy shifts equilibrium level, location, and technological composition of entry in the context of the Texas electric grid, where these dynamics are particularly relevant. Texas has ample wind and sunlight resources. It also builds new electric transmission infrequently. These two features of the market came to a head during the 2018 to 2024 period, when fixed costs for wind and solar generators dropped and both technologies entered rapidly. Grid capacity remained mostly fixed throughout the period and grid congestion increased. The incidence of this congestion was unequal: generators stuck behind congested transmission lines saw revenues fall, while generators in uncongested regions of the grid earned steady revenues. The geography of resource quality made this particularly punishing for wind generators – while solar generators had access to reasonably high quality sunlight throughout the state, high quality wind resources were located in the panhandle and central Texas, gated behind congested transmission elements.

I begin by illustrating the core economic tradeoffs within a simplified three-node model of the electric grid. I briefly discuss the physics of grid operation and locational pricing on the grid, showing in particular how entry in one node can cause congestion on distant transmission lines. This phenomenon is referred to in the literature as a loop flow and can be very costly for incumbent generators. I then discuss how current policy leads to a coordination inefficiency when generators decide on entry. The issue arises when generator entry and infrastructure improvements are solved for separately: when infrastructure is scarce, generators enter locations less likely to experience congestion. These decisions trade off production for congestion relief. The trade off reduces the value of new infrastructure, as realized entry decisions make use of the existing grid. I show that this leads to inefficient outcomes, where welfare would be higher if generators entered in resource rich locations and the grid operator built infrastructure to support that entry.

Next, I test how infrastructure availability shapes generator entry decisions. I solve a dynamic entry game among renewable generators, where generators differ in their technology

and their location on the grid. Entrants are forward-looking and make decisions based on the expected evolution of entry both in their own region and in other regions. The entry model has 40 regions, which span the service territory of the Electric Reliability Council of Texas (ERCOT), the grid operator for Texas. Each period, a fixed number of potential entrants arrive in each region and decide on entry. Regions vary in the quality of resource they have available and the expected price that entrants will earn from producing in that region, among other factors. Resource quality is exogenous and fixed; regional prices and quantities are endogenous. Entrants make decisions based on expected profits, weighed against the fixed costs of entry for a given region and a cost shock. I treat ERCOT’s infrastructure policy as a fixed grid policy with no transmission capacity improvements, consistent with the level of improvements ERCOT made to the grid over this period.¹

Prices on the electric grid depend on the flows of electricity throughout the network. Solving the entry game while accounting for evolving wind and solar generation in all 40 regions would require a computationally infeasible state space. Instead of solving the full game, I solve a simplified game, where entrants form beliefs about other-region entry based on equilibrium entry policies and integrate over potential spatial allocations of generation that cost shocks could justify. This preserves the network structure of prices: entry in one region affects prices everywhere. In equilibrium, entrant beliefs align with the stationary distribution of generation allocations, meaning that entrant expectations about prices are accurate within the model.

The analysis is built on a newly assembled dataset, featuring detailed information on generation, transmission capacity, and demand for the Texas electric grid. I combine these data to solve the grid operator’s dispatch problem. The generation data includes detailed information on generator cost curves, which is what the grid operator minimizes when deciding on dispatch. The transmission capacity panel recovers the transmission line-specific flow limits, the first key constraint in the dispatch problem. I develop a procedure to disaggregate zonal demand data to the county level so I can capture system- and county-level demand at the hourly level, which the grid operator also must satisfy in the dispatch problem. I embed the dispatch model within the entry model, using it to calculate flow profits for entrants. Entry further depends on fixed costs, which are estimated based on a panel of shifters that vary at the technology-county-year level.

The entry model confirms that loop flows are costly for some incumbent generators.

¹ERCOT frequently makes reliability focused upgrades to the grid, which are initiated based on concerns about line overloading and more commonly targeted at the lower-voltage distribution grid. On rare occasions, ERCOT has made substantial upgrades to its high-voltage transmission grid. A significant upgrade was made in 2014; more recently, proposed 765 kV transmission lines have been met with stiff political and popular opposition. I abstract away from the more political processes that govern these decisions.

I calculate how entry shifts the average congestion costs that incumbents pay when they produce. I find significant heterogeneity in the incidence: in the far west and south Texas regions, loop flows increase congestion costs by almost \$1/MWh – a roughly 5.5% decrease in yearly revenue. In regions closer to load and downstream of congestion, loop flows have minimal effects.

Next, I ask whether alternative transmission policies would lead to welfare-improving allocations of generation on the grid. To test the effect of each policy, I implement the new policy, compute a new equilibrium, and then solve for the evolution of entry and the grid from 2018 through 2024. I assess the effect of the policy based on welfare. I also note the effect on prices.² I implement two alternative policies: first, a policy that requires entrants upgrade the grid themselves, which I refer to as the upgrade-on-entry policy; and second, a policy where entrants, incumbents, and consumers submit bids for new infrastructure, which I refer to as the market for transmission. Each policy targets the coordination inefficiency to varying degrees of effectiveness.

I find that upgrade-on-entry elicits demand for new transmission, but imposes costs of entry that are too high and borne exclusively by entrants when new transmission also benefits incumbents. This pushes entry away from better resource quality areas in central and west Texas and towards demand centers in east Texas. It also increases solar entry over the baseline policy, but greatly decreases wind entry. This reduces welfare by \$2.7 billion relative to the Texas baseline.

I find that the market for transmission builds less infrastructure than upgrade-on-entry policy. The market gives the grid operator a way to elicit entrant, incumbent, and consumer values for new transmission. Doing so reveals that some upgrades initiated under upgrade-on-entry are more costly than the congestion they alleviate. Results show that jointly solving for entry and transmission provision reduces the entry distortions across technologies and locations, leading to a spatial reallocation of solar entry towards high-resource quality regions. The market delivers slightly lower welfare than the baseline policy because it builds less renewable generation and thus emits more CO₂.

Together, my results suggest three takeaways: (i) infrastructure availability distorts generator entry decisions at the technology and location levels, and on the Texas grid, induces over-entry of solar generation in places with poor resource quality; (ii) upgrade-on-entry – the dominant infrastructure policy in most of the U.S. – imposes inefficiently high costs on entrants, inadvertently exacerbating the entry distortion and reducing welfare relative to Texas’ baseline policy; and (iii) policies that coordinate between generator entry and infrastructure provision can fix entry distortions induced by insufficient infrastructure. I close by

²I assume demand is perfectly inelastic, so prices are not accounted for in welfare.

discussing how a market for infrastructure is particularly well-suited to situations where the location of future demand is uncertain because it elicits latent demand for infrastructure from actors that benefit from the infrastructure.

Literature Review

New economic geography asks how economic forces shape the geography of production (see, e.g., Krugman, 1991 and the papers that followed Krugman and Venables, 1995; Venables, 1996) and how trade costs can shape the diffusion of technology (Desmet and Rossi-Hansberg, 2014). More recently, the literature has taken models from new economic geography to real-world data, seeking to understand how forces of agglomeration and dispersion lead to the geography of production we see today (Redding and Rossi-Hansberg, 2017). A smaller literature has focused on how infrastructure specifically is linked to growth and welfare (Fernald, 1999; Duranton and Turner, 2011). This paper considers how infrastructure determines firm entry to the market, leveraging techniques from empirical industrial organization (Seim, 2006; Jia, 2008) to answer how specific infrastructure improvements determine the equilibrium location of firms. The approach is similar to Sweeting (2013) or Wollmann (2018), where firm product portfolios are a function of the competitive landscape in which they operate.

I model the grid operator’s problem, accounting for flows of electricity across individual transmission lines. The model I use is closest in spirit to Gowrisankaran et al. (2016), who estimate the grid operator’s problem in Tucson, Arizona. I add to their model a focus on electricity flows. Previous work has primarily modeled power flows on the grid as a series of point-to-point connections (Arkolakis and Walsh, 2023; Golden, 2026); I extend this approach to consider a network representation of the grid and derive realistic prices at the county level. My representation of congestion is very similar to Boatwright (2025), who models the effect of congestion on entry in the Texas grid as well. I focus on effect of loop flows (as described in De Cannière (2026)) and a coordination inefficiency, which is similar to a feedback loop described in Pozo et al. (2013); Mays (2023). I add to these papers the first embedding of a realistic dispatch model within a dynamic entry game.

I make two main methodological contributions to the electric grid literature: first, I illustrate how existing data can be used to estimate an accurate model of electricity dispatch. The data I use is all publicly available and hand-collected. The second methodological contribution is the representation of the electric grid that I embed in the dynamic entry game. Whereas traditional approaches to high-dimensional dynamic games rely on Markov Perfect strategies (Ericson and Pakes, 1995) or oblivious equilibria (Weintraub et al., 2008), I use aggregate quantities of wind and solar generation on the grid and beliefs over how those

quantities are allocated across regions to capture regionally-varying price expectations. This approach follows Ifrach and Weintraub (2017).

This paper is part of a rapidly growing literature on the benefits and underprovision of electric transmission. Prior work has studied the value of transmission in a variety of settings, including the Midwest, Texas, Chile, and the continental U.S. (Borenstein et al., 2000; Fell et al., 2021; Gonzales et al., 2023; Arkolakis and Walsh, 2023; Hausman, 2024; Holland et al., 2024; Boatwright, 2025; Golden, 2026). These papers show that transmission increases allocative efficiency, decreases emissions, and increases long-run investment in renewable capacity. Despite widespread agreement as to the value of new transmission, underinvestment in transmission persists. In counterfactuals, I endogenize the transmission planning process, connecting this literature to an older literature that theorized about transmission planning policies for grid operators (Léautier, 2000; Vogelsang, 2001; Joskow and Tirole, 2005; Hogan et al., 2010). These papers recognize the difficulty in incentivizing efficient expansion of the transmission grid, showing how underinvestment in transmission arises. The most efficient policy I consider in counterfactuals, a market for transmission, is similar in spirit to Chao and Peck (1996), who design a market for transmission. I build on their model by establishing a market for transmission that explicitly accounts for generator entry.

The rest of the paper is structured as follows: Section 1 introduces the setting. Section 3 introduces the dynamic entry model, while Section 4.3 describes how I estimate the model. Section 5 describes the entry model results and Section 6 introduces the counterfactuals and the results I find. Section 7 concludes.

1 Background

The Texas electric grid, operated by ERCOT, is an independent power grid, meaning that the vast majority of electric generation demanded by Texas consumers is met by Texas-based generators (Cohn, 2022).³ As system operator, ERCOT is responsible for balancing supply and demand for electricity on the grid, which it accomplishes by scheduling when and how much electricity individual generators should produce. There are more than 1,460 generators in ERCOT’s territory (Electric Reliability Council of Texas, 2026).⁴ Electricity in ERCOT is transported using high-voltage alternating current transmission lines that link the resource-rich, low-demand regions in the western part of the state to high-demand population centers in the east.

³Texas has two transmission lines connecting it to the Eastern Interconnection and two transmission lines connecting it to Mexico; these lines are primarily used for scheduled and emergency power trades.

⁴Moving forward, I refer to ERCOT’s territory as ERCOT for simplicity.

In the short-run, demand for electricity is highly inelastic. Every five minutes, demand for electricity (referred to as load) is reported by utilities and wholesale consumers. Generators themselves submit bid curves to the grid operator, reporting the amount of electricity they are willing to provide at different prices.⁵ Balancing supply and demand then requires the grid operator solve a constrained optimization problem: given demand for electricity, find the least-cost dispatch of electricity generation subject to transmission capacity. The optimization problem solves for production across the entire grid at once, solving for production and demand at precise geographical resolutions.⁶

Constraints in the optimization problem include transmission line capacity. Once lines become congested, the grid operator is forced to dispatch electricity from nodes with higher cost than the system cost and curtail electricity production from nodes with lower cost than the system cost.⁷ In nodes where generators are curtailed, the local price (LMP, or locational marginal price) falls below the system price of energy. LMPs indicate what the marginal generator in a node is willing to produce electricity for. In nodes on the demand side of congestion, prices will rise above the system price of energy, as marginal generation in that node has to turn on to meet demand.

ERCOT is responsible for setting generator entry policy. ERCOT uses a unique policy among American grid operators, where generators connect freely to the grid, whether or not the transmission capacity exists for them, and take on the risk of curtailment as a consequence (Trabish, 2025).⁸

Grid upgrades are centrally planned in ERCOT. Generally, utilities are responsible for identifying and proposing new upgrades, while grid operators retain final approval authority. Utilities earn a regulated return on these grid investments, with rates subject to review by Public Utility Commissions. Recent studies have found that transmission planning is falling far behind generation growth and, more recently, load growth (Congressional Budget Office,

⁵I assume generators report costs honestly. Independent market monitors are appointed to each grid operator to ensure that reports are honest. Market monitors are able to access internal generator data and grid operator data to ensure that generators are not manipulating their offers.

⁶The problem is solved at individual nodes of the transmission grid. Nodes are the point at which electricity moves from generators to the transmission grid and the point at which demand is settled for a small area. There are several thousand nodes in ERCOT.

⁷Curtailment is when a generator has to throw away the electricity it produces because there is insufficient transmission capacity to carry the generator’s electricity to demand.

⁸Most other grids use an “invest-and-connect” process, which I approximate with the “upgrade-on-entry” policy adopted in counterfactuals. When a generator enters the grid, the operator initiates a study process to identify any overloads that the generator might cause and suggests a series of improvements to the grid that the generator should make to avoid grid congestion in summer peak, winter peak, and light demand scenarios. The generator must then make investments to improve the grid before it can enter. The scope of the upgrades that a generator must make thus depends on the location it chooses: locations with poorer local transmission capacity are more likely to trigger expensive upgrades. The grid is public infrastructure and investments are non-rival up to grid capacity.

2026). Today, 90% of upgrades are focused on reliability (i.e., avoiding transmission line overloads), instead of economic benefits (i.e., reducing congestion costs).

The entry of renewables in ERCOT between 2018 and 2024 led to unprecedented congestion, with yearly congestion costs reaching a high of \$2.8B in 2022 (Shreve et al., 2025).⁹ Transmission upgrades have not kept pace with the renewable capacity and transmission availability has decreased as a result. Table 1 shows the yearly congestion costs and transmission line miles upgraded in ERCOT (where upgrades represent increased transmission capacity). The table subsets transmission line upgrades to 230 kV and higher capacity lines, of which there are 18,446 miles on the grid. Across the seven year period, roughly 5% of transmission lines received an upgrade.

Table 1: Transmission Congestion Costs and Transmission Line Upgrades

	2018	2019	2020	2021	2022	2023	2024
Congestion costs (\$ millions)	1,260	1,260	1,400	2,100	2,800	2,400	1,900
Transmission Line Upgrades (miles)	292	0	0	373	0	213	121

Notes: Congestion costs are in millions of dollars and come from Table B1 of Shreve et al. (2025). Transmission Line Upgrades measures completed new 230 and 345 kV circuits, including new corridors and additional circuits on existing corridors. Rebuilt lines, station work, and generator interconnection facilities are excluded.

The technology mix of generation in ERCOT has changed dramatically in recent years. Figure 1(a) shows generators that operated in ERCOT in 2000. Generators clustered around major urban areas and industrial load zones like the Gulf Coast. Electric generation mostly came from dispatchable resources like coal and natural gas. Dispatchable resources are significant in that the amount of electricity they generate is a choice - if the grid needs more electricity, dispatchable resources can increase their production until they reach their high sustained limit, which is a function of their nameplate capacity.

Figure 1(b) shows generators that operated in ERCOT in 2024. The rise of renewables in ERCOT has been remarkable. Whereas coal and gas represented 92% of capacity in 2000, they represent 53% in 2024. Renewables represent 38% (U.S. Energy Information Administration, 2026).¹⁰ The majority of renewable additions have come since 2017, following dramatic decreases in solar fixed costs and generous tax incentives for the development of wind power (U.S. Energy Information Administration, 2026).

While transmission upgrades were rare over the period I study in this paper, ERCOT

⁹Congestion costs are based on congestion rents, measured as the difference in price between two locations times the amount of power flowing on the transmission line connecting the locations.

¹⁰Renewables produced 34% of energy consumed in ERCOT in 2024 because they only infrequently produce at full capacity (Electric Reliability Council of Texas, 2025).

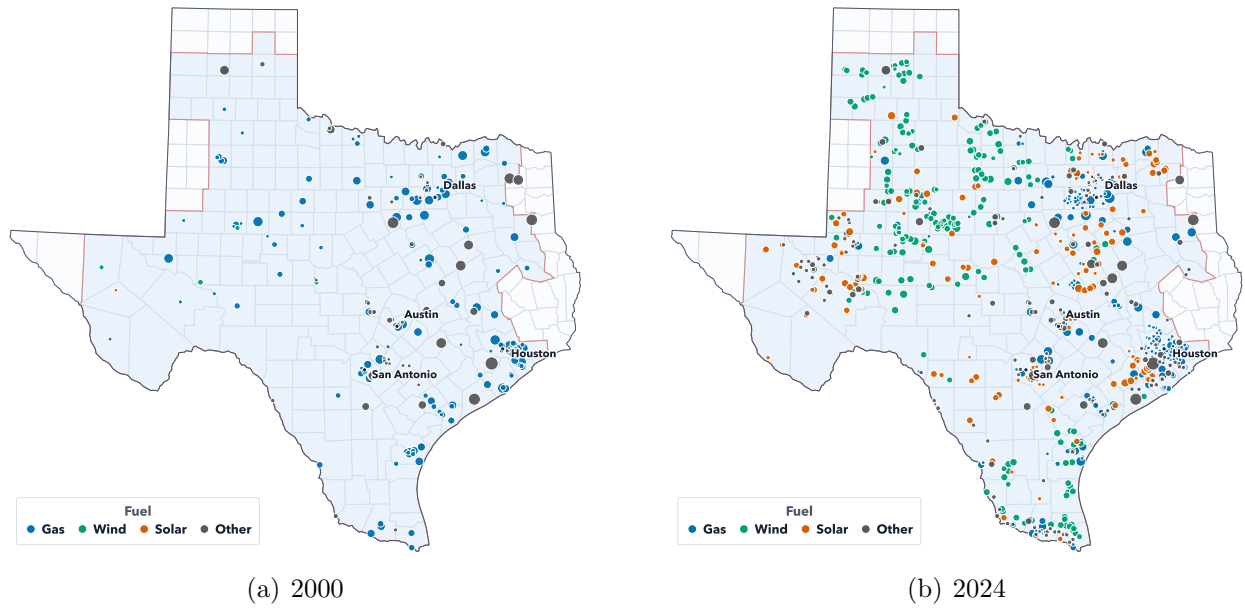


Figure 1: ERCOT generating capacity, 2000 and 2024

Notes: Each point represents a generating facility. Marker area scales with nameplate capacity, and color denotes the facility's dominant fuel category. "Other" includes coal, nuclear, hydroelectric, biomass, storage, and other fuels. Pale-blue shading denotes counties in ERCOT; the light-red line traces the resulting county-level ERCOT boundary. Data come from the historical EIA-860A/B inventories for 2000 and the final EIA-860 2024 release.

made changes to its grid to support renewables in 2014, when it finished building the CREZ transmission lines.¹¹ The CREZ lines are high capacity transmission lines that link wind-rich regions like the panhandle and central Texas to demand centers in the eastern part of the state. The CREZ lines spurred development of wind generation in Texas (Jankovska and Cohn, 2020). Wind entrant locations shifted once they were built: pre-2014, the MW-weighted average distance between wind entrants and Texas’ major demand centers (Dallas-Fort Worth, Houston, Austin, and San Antonio) was 197 miles; in 2014, additions were located a MW-weighted average of 285 miles from demand centers.

Renewables continued to enter in the years following the CREZ lines. The MW-weighted average distance to demand centers for wind generators in 2018 was 208 miles. For solar, it was 212 miles. The congestion that arose during the 2018 through 2024 period generated very different equilibrium entry patterns for wind and solar generators. In 2024, wind generators located, on average, 189 miles from demand centers. Solar generators on the other hand located 148 miles away from demand centers, a 30% decrease in average distance relative to 2018, when congestion costs were lower.

2 Illustrative model

In this section, I present a three-node model of the electric grid that illustrates the key inefficiencies that I study.

Figure 2 shows a simplified three-node network of the grid. Load is located exclusively in the East node, indicated with a house icon. There are two generators on the grid: a natural gas plant in the East node and wind generator in the West node. There is neither demand nor generation at the South node. Wind generator production costs are zero, while the gas generator has constant and positive production costs.¹² There are three transmission lines: a WE line, a WS line, and a SE line. I assume each line has the same total capacity. I assume that renewable production is highest at the West node, intermediate in the South node, and zero at the East node.

The grid operator’s problem consists of minimizing the cost of generation such that demand in the East node is satisfied and flows on each transmission line are less than the line’s capacity. I assume that total demand is larger than maximum capacity of the wind generator, meaning the gas generator is used in dispatch. The price in each node is equal to the marginal benefit of increasing generation at that node by one MW. In this example,

¹¹At the time of CREZ, solar capital costs were too high to be competitive as a utility electricity source in Texas, so the CREZ lines were primarily situated to facilitate wind generation.

¹²Gas generators typically have increasing production costs in the data. Using constant production costs here simplifies the analysis, at the cost of understating the inefficiency I describe below.

increasing generation in the West node displaces one MW of gas generation, meaning the price in the West is equal to the production cost of gas. The same principle holds at the South node (though, without any generator located in the node, neither demand or nor supply participates in the market at the node) and in the East node. The result is that prices are common across all nodes.

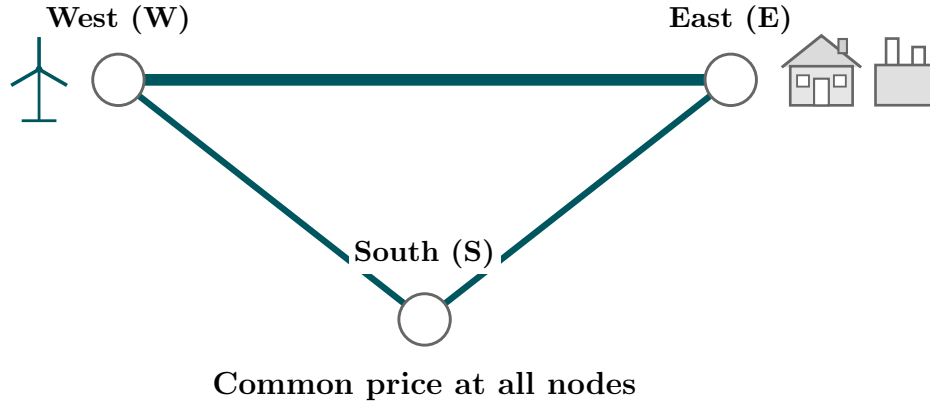


Figure 2: Illustrative three-node network

Flows of electricity across each transmission line are shown by the thickness of the transmission line. Transmission line flows depend on line characteristics and the distance that electricity has to travel to go from the generation node to the demand node along that path. The physical laws that govern electrical flows are referred to as Kirchhoff's Laws (Stott et al., 2009). I assume that line characteristics are identical in this example. Flows, then, depend only on distance: WE has a distance of one, and WS-SE has a distance of 2. As a result, twice as much electricity flows on WE as flows on WS and SE. I describe the precise way that I measure electricity flows in Appendix B.

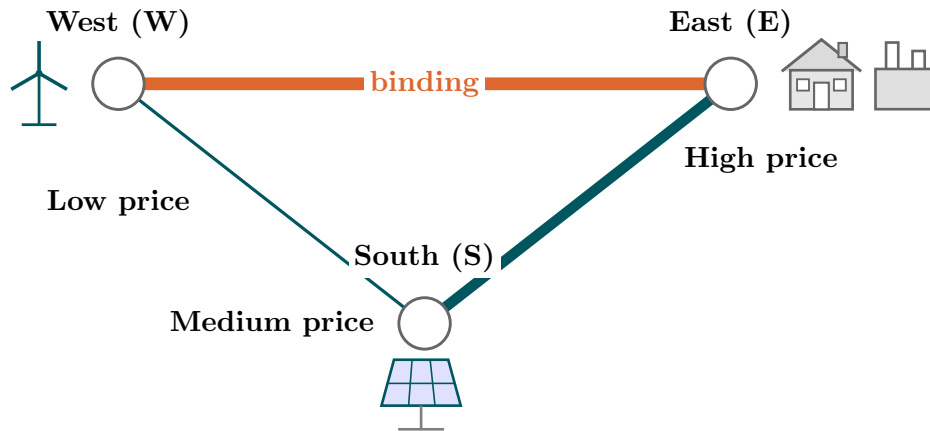


Figure 3: Three-node network after solar entry

I now consider the dispatch problem when a solar generator enters in node S. The situation is shown in Figure 3. The solar generator’s electricity flows follow the same pattern as the wind generator’s: one-third of its production travels via SW-WE and two-thirds travels via SE. Letting Q_j represent the production in node j , the total flows on line WE are $\frac{1}{3}Q_S + \frac{2}{3}Q_W$. In the example shown, using the wind and solar generators to full capacity overloads the WE line.¹³ The line then binds in the grid operator’s cost minimization problem, leading the grid operator to redispatch generation such that the line does not overload. This illustrates how entry in one node can have far-reaching consequences, causing congestion on lines that are not directly connected to the entrant’s node.

Prices adjust following the congestion. Incremental demand in the East node is still met by the gas generator, keeping prices high. Prices in the West node, however, fall precipitously: adding one MW of generation in the West serves no additional demand because it cannot reach the East node. The price in the West thus drops to the production cost of the wind generator, which in this case is zero. This effect, where production leads to congestion on unconnected transmission lines, is referred to as a loop flow. Notably, it greatly increases the value of transmission for incumbents who are adversely affected.

Prices in the South node are intermediate. Adding one MW of generation in the South sends some electricity along the uncongested SE line, displacing costly gas generation. The rest of the electricity travels through the binding WE line, increasing congestion and requiring less wind is dispatched, which is costly to the grid. The marginal benefit of generation in the South is thus greater than zero but less than it would be in an uncongested grid.

Most objects in the simplified example are available directly in the data. Transmission line geometry and voltage as of 2024 is available from the Homeland Infrastructure Foundation Level Data resource. Generator county information is available in ERCOT’s MORA reports. Generator supply curves are reported by ERCOT, using its SCED (Security Constrained Economic Dispatch) data. Load is available at the zonal level. Congestion data (including the substations between which congestion arose and the cost of that congestion for the grid) is available. I map congestion data to transmission line geometry by hand-encoding the location of relevant substations. Transmission line capacity is unobserved. I estimate capacity based on implied flows using generator supply information, congestion data, and the reactance assumptions. Together, these objects constitute what I call the dispatch model, the construction of which is detailed in Appendix B.

¹³Note that this result relies on production being higher in the West node than it is in the East node. If the geography of production was reversed, the SE line would bind before the WE line.

2.1 Coordination Inefficiency

Now, I consider the solar generator siting problem. I assume that potential solar generators in nodes S and W face entry decisions. I assume that a solar generator in node W produces 25 MW and a generator in node S produces 20 MW (reflecting better sunlight resources in node W). I assume the production cost for gas is \$30 and the production cost for solar is \$0. I assume that total electricity demanded is 120 MW, and that a 40 MW wind farm is located in node W and a 100 MW gas plant is located in node E. Let entry impose a fixed cost of 200 on the generator and upgrading line WE cost 250. Let the upgrade be large enough to remove the constraint if one generator enters. Table 2 summarizes the resulting profits and welfare.

Table 2: Solar siting and transmission-upgrade payoffs

Solar location	No WE upgrade		Upgrade WE	
	Solar profit	Welfare	Solar profit	Welfare
South (S)	100	250	400	150
West (W)	−200	−50	550	300

Entering S without an upgrade is profitable for the solar generator. $2/3$ of its 20 MW travel to load via line SE, while $1/3$ travels via SW-WE. This leads to an overload on line WE: $20/3 + 80/3 > 30$. To prevent the line from breaking, wind generation is curtailed and produces 35 MW instead of 40. Because wind is curtailed, marginal generation has no value, and the price at node W drops to \$0. Adding 1 MW of generation to node S has two effects: first, it delivers $2/3$ MW of electricity via line SE. Second, it adds $1/3$ MW of electricity to line WE. This again causes the line to overload, necessitating that wind generation at node W drop by $1/2$ MW. Since $1/3$ of the $1/2$ MW decrement travels via WS-SE and no new electricity travels via WE, the net delivery from a 1 MW injection at node S is $2/3 - (1/3 \times 1/2) = 1/2$. The price of electricity at node S is thus \$15, because it displaces $1/2$ MW of \$30 gas in node E. Finally, the price of electricity in node E stays at \$30, which is the marginal cost of gas generation.¹⁴

Entering W without an upgrade worsens congestion on the grid, meaning the solar generator earns \$0 for its production. The solar generator provides 5 MW of production to the grid that previously did not exist, displacing 5 MW of gas generation for a benefit of 150. Because the solar generator pays 200 to enter, net welfare change is −50.

¹⁴I formally derive the grid operator's constrained optimization problem in Appendix B.

Upgrading WE changes payoffs and welfare. With an upgrade, prices are equal at each node. Gas is still the marginal generator in each scenario, meaning prices are \$30 in all cases. If the solar generator enters S, it produces 20 MW. It earns $20 \times 30 - 200$. Welfare is equal to 150 because solar displaces 20 MW of gas, but the solar generator pays its fixed entry cost and the line upgrade costs 250. If the solar generator enters W, it produces 25 MW, earning $25 \times 30 - 200$. Welfare increases accordingly.

Immediately, this introduces a coordination problem: the solar generator only enters W conditional on the upgrade existing. But once the solar generator enters S, the upgrade reduces welfare relative to the no-upgrade world. Thus, achieving the first-best outcome requires jointly deciding on infrastructure provision and entry locations. Current grid construction policies prevent this coordination from occurring.¹⁵ This issue is present with wind generation too: solar generators faced a fairly gentle reduction in supply when locating in S. For wind generation in ERCOT, that penalty is much steeper, making entry unprofitable at any location without an upgrade.

Note that the results in this section are not unique to the electric grid. While a complex interaction of power flows leads to congestion on the electric grid, the same locational and technological distortion would flow through if electric transmission functioned like a pipeline, where flows could be directed by a system operator.

3 Entry Model

This section details the empirical model of generator entry that I estimate. Agents in the model are renewable generators. I treat generators as technology-specific, independently operated, single-plant firms.¹⁶ I fix entrant sizes to the average nameplate MW of wind and solar entrants from 2018-2024. Each period, generators make a single decision in the model: enter or permanently forgo the opportunity. I omit transmission line upgrades, reflecting the limited number of bulk transmission grid improvements ERCOT made over this period. I return to the upgrade process in counterfactuals.

Generator payoffs are the lifetime sum of the price they earn and the quantity they produce across hours in the dispatch model. Both prices and quantities are endogenously determined within the dispatch model; maximum production for each generator additionally depends on the resource quality of the region in which they are located. The solution to the

¹⁵While I model ERCOT's policy as a fixed grid policy, on the occasions when it makes a grid investment for economic reasons, it does so based on static cost-savings.

¹⁶Joint ownership is permitted in ERCOT (Electric Reliability Council of Texas, 2022). Johnston et al. (2024), looking at the Pennsylvania-Jersey-Maryland grid, report that the largest developer in their sample holds 4.3% of all projects and that the 15 largest developers jointly hold under 32% of projects.

dispatch problem depends on the location and maximum production of each generator on the grid. This presents an issue for entering generators, who need to know about the location of generation on the grid to generate expected prices, but for whom keeping track of individual generators on the grid would be computationally infeasible. I model the generator’s entry problem by solving for beliefs about other-region entry that are consistent with solved entry policies in other regions. Generators pay fixed costs upon entry and receive a cost shock when deciding on entry. I model production costs for renewables as zero.

The model is solved in three steps. First, I find a fixed point in entry policies and the payoff firms receive upon entering. Next, I solve for beliefs about other-region entry that are consistent with entry policies. Then, I recover the fixed cost threshold implied by the model and project that threshold onto the fixed cost shifters, which vary at the region, technology, and yearly level. Finally, I choose a variance for the fixed cost shock that minimizes the distance between observed and model-implied entry probabilities.

Equilibrium in this model is driven by the tradeoff between resource quality and dynamic congestion concerns. As congestion becomes more likely and more costly, this tradeoff becomes more acute. Capturing these dynamics requires a representation of renewable capacity on the grid and where that capacity is located. Following Weintraub et al. (2008) and Ifrach and Weintraub (2017), I solve for a stationary moment-based Markov equilibrium (MME) where firms track the spatial allocation of rival capacity. Generators include details about their own region (renewable capacity) and a statewide summary of total renewable capacity according to their technology on the grid.

3.1 Timing

Entrants face site-specific entry opportunities, so the entry decision is at the region-technology level. Regions in the model are county clusters – there are 40 regions in total and each region has on average six counties within it.¹⁷ The number of generators of each technology τ eligible to enter each region r each period, $\bar{N}_{r\tau}$, is fixed at the largest number of region-year entrants seen in the region across all years plus one. Solar and wind generators made up the vast majority of entrants to the grid over the period I study, though battery storage entered in large quantities in 2023 and 2024. I treat new non-solar or wind entrants as exogenous shifts in supply.

¹⁷Regions are generated based on edge characteristics, assessed on distance (smaller distances are better), capacity similarity (high-capacity corridors are grouped together), and congestion frequency (congestion separates regions). The goal is to cluster counties with limited intraregional congestion into a larger region. Implicitly, this says that when generators site in that region, intraregional deliverability is more robust than cross-region deliverability.

Each period represents one year. The timing of the model proceeds as follows:

1. States and beliefs are realized. Entrants draw T1EV i.i.d. cost shocks and simultaneously decide on entry.
2. Retirement is realized. If chosen for retirement, generators exit. Generator entry occurs.
3. Production occurs for all studied hours using transmission capacity and supply curves constructed based on regional technology quantities. Payoffs accrue to generators and states transition.

Publicly observed state variables are given by $x_{r\tau}$:

$$x_{r\tau} = \{q_{r,\text{solar}}, q_{r,\text{wind}}, Q_{\text{solar}}, Q_{\text{wind}}\},$$

where r indicates the region in which an entrant is located, τ indicates the entrant's technology type, $q_{r,\text{solar}}$ indicates the quantity in MW of solar generation in r , $q_{r,\text{wind}}$ indicates the quantity in MW of wind generation in r , and Q_τ indicates the total quantity in MW of each technology type on the grid. I omit the subscripts on x moving forward for clarity.

Instead of tracking the quantity of supply across all regions and for all technologies, entrants form beliefs over the allocation of Q_{solar} and Q_{wind} across the grid. g represents the true allocation of capacity. It determines LMPs, based on the spatial pricing mechanism that I discussed in Section 2. Entrants evaluate payoffs and transitions under the equilibrium conditional belief $M(g | x)$. The remaining beliefs depend on $p(x)$: q transitions according to realized entry counts and retirement. Q evolves under entry implied by $p(x)$.

The model is infinite-horizon and stationary. I assume that entrants play the same strategy each year conditional on the state. Demand in ERCOT rose by roughly 2% per year between 2018 and 2024. I solve for strategies using demand realizations from 2018 because sampling hours across years thus risks asking 2018-level capacity to meet 2024-level demand, which would lead to blackouts. There were also regional shifts in demand in ERCOT over this period. Oilfield electrification in the Far West led to localized demand doubling in the region and increased congestion. I cannot capture anticipatory entry in my model. I return to this in Section 5.

Changes to fixed costs (along with state variable transitions) drive new entry behavior each year. I treat these shifts as unexpected by entrants. The changes are driven by decreasing capital costs (solar) and shifting tax policy (wind). There is evidence that entrants may anticipate changes to tax policy, which could make it more difficult for me to pin down correct entry strategies (Chen, 2025).

3.2 Entry

Each period t , a new set of entry opportunities $\bar{N}_{r\tau}$ appears in each region. Entrants decide whether they would like to pursue the entry opportunity $a_{r\tau} = 1$ or let it lapse $a_{r\tau} = 0$. Entry opportunities within a region-technology type are symmetric, thus all entrants play the same mixed strategy entry policy $p(x)$. Entrants must pay a fixed cost $F_{r\tau}$ to enter. Entry decisions are made simultaneously.

Entrants are forward-looking and make decisions about entry based on flow payoffs along with future grid evolution, implicitly trading off the resource quality of a location against its current and future expected transmission congestion. They observe the public moment state x and a vector of private shocks $\{\epsilon_{0r\tau}, \epsilon_{1r\tau}\}$, which I assume follow the T1EV distribution with scale parameter σ_τ . They do not condition their entry decision on the full other-region allocation g ; instead, they hold equilibrium beliefs $M(g | x)$ over the allocations consistent with the observed moment state. I discuss how entrants form $M(g | x)$ in Section 3.2.1.

Let β be the annual discount factor, common to entrants and incumbents. Let x' indicate next period's state realization, $E_{p,M}^{inc}$ indicate the expectation for an incumbent over entry policy p and capacity allocation belief M and $E_{p,M}^{ent}$ indicate the expectation for an entrant. Let $\pi_{r\tau}$ denote the technology-specific flow payoff for a given x and g realization. Then, for a given entry policy p and allocation belief M , the value of a generator of type τ in region r on the grid $V_{r\tau}(x)$ and the value of entry $v_{r\tau,1}(x)$ are given by:

$$V_{r\tau}(x) = E_{p,M}^{inc}[\pi_{r\tau} + \beta V_{r\tau}(x') | x] \quad (1)$$

$$v_{r\tau,1}(x) = E_{p,M}^{ent}[\pi_{r\tau} + \beta V_{r\tau}(x') | x, a_{r\tau} = 1] \quad (2)$$

For a generator of technology τ in region r already on the grid, the value of being on the grid depends on the generator's production profile, which depends on τ , rival generator entry in all regions, given by p , and the generator's belief about how capacity is allocated across other regions, given by $M(g|x)$. Then, retirement is realized and dispatch is run, generating $\pi_{r\tau}$. The value of entering is almost identical, except the entrant needs to account for how its own entry affects state variables $q_{r\tau}$ and Q_τ and dispatch realizations.

Entrants weight the value of entry against fixed costs and cost shock realizations:

$$\tilde{v}_{r\tau,1}(x) = v_{r\tau,1}(x) - F_{r\tau} - \epsilon_{1r\tau} \quad (3)$$

$$\tilde{v}_{r\tau,0}(x) = -\epsilon_{0r\tau} \quad (4)$$

Let $p_{r\tau}(x)$ denote the entry probability for a technology- τ region- r opportunity in state x , and let $p \equiv \{p_{r\tau}\}_{\tau \in \mathcal{T}}$ denote the complete entry-policy profile. Projects enter when

$\tilde{v}_{r\tau,1}(x) \geq \tilde{v}_{r\tau,0}(x)$. T1EV shocks yield the logit entry probability:

$$p_{r\tau}(x) = \frac{\exp([v_{r\tau,1}(x) - F_{r\tau}] / \sigma_\tau)}{1 + \exp([v_{r\tau,1}(x) - F_{r\tau}] / \sigma_\tau)}. \quad (5)$$

σ_τ controls the scale of the cost shock that entrants receive. Small σ_τ values indicate that entry is fairly deterministic conditional on the modeled value of entering in a region, while large σ_τ values indicate substantial unobserved heterogeneity in entry costs. I describe the process I use to estimate σ_τ for each technology in Section 4.3.

$p(x)$ gives the entry policy that generators play. Inverting Equation (5) yields a closed-form representation of fixed costs:

$$F_{r\tau} = v_{r\tau,1}(x) - \sigma_\tau \log\left(\frac{\hat{p}_{r\tau}(x)}{1 - \hat{p}_{r\tau}(x)}\right). \quad (6)$$

$\hat{p}(x)$ is observed entry frequencies. I then parameterize the model-implied fixed costs according to observable fixed cost shifters, including capital costs, tax rebates, land costs, and a local Texas tax rebate that I discuss in Section 4. I aggregate capital costs, land costs, and tax rebates into a $C_{r\tau}^{\text{net capex}}$ value, while I include other non-price shifters in $Z'_{r\tau}$, which I discuss in more detail in Section 4.3. Letting θ_τ hold the coefficients for all non-price shifters, the parameterization is as follows:

$$F_{r\tau}(\theta_\tau) = C_{r\tau}^{\text{net capex}} + Z'_{r\tau}\theta_\tau. \quad (7)$$

The coefficients on this cost function are estimated using observed entry choices and model-generated entry values. The coefficient on net capex is fixed to one because it is measured in dollars. Projecting fixed costs onto observables provides a common fixed cost function for counterfactuals.

3.2.1 Beliefs

Forecasting payoffs requires more than the observed states. Consider, for example, $q_{r,\text{solar}} \ll Q_{\text{solar}}$. If solar generation outside region r was uniform across all other regions, congestion would be low in region r . If outside solar generation was instead concentrated in a single region, congestion would be rampant on the grid and prices in r would either be very low (if it was further from demand than the concentrated region) or very high (if it was closer to demand than the concentrated region). These situations, too, are not equally likely: other-region entry concentrating in a single region would be uneconomic. Entrants have beliefs over g , which is the full county-level allocation of generation. The belief over entry

allocations $M(g|x)$ provides the distribution of g that is consistent with x for each x (Ifrach and Weintraub, 2017).¹⁸ In effect, entrants have a distribution of potential other region quantities for each Q that corresponds to how often that allocation of quantities would occur under the solved entry policy $p(x)$ and retirement.

In the equilibrium, M must coincide with the stationary allocation distribution of generation. Because p shifts entry probabilities, it shifts M : when equilibrium entry shifts in a given region, beliefs about other-region entry must also shift. To ensure this is the case, beliefs are initialized at a random allocation. $\bar{N}_{r\tau}$ entrants then appear in each region. Each potential entrant receives a cost shock u and enters if $u < p(x)$. This follows the forward simulation method from Ifrach and Weintraub (2017).

Following entry decisions (and retirement), g transitions $g' = T(g_M, u; p)$; q transitions $q' = \sum_{c \in r} g'_c$; and Q transitions $Q' = \sum_r q'_r$. This yields x' . I update M , where the new M contains a dampened combination of original allocations and destination allocations observed following state transitions.¹⁹ Having a new M distribution shifts implied p and V values, thus restarting the values and entry policy loop. I continue updating p , V , and M until a stationary equilibrium is reached.

3.3 Retirement

I assign each generator an exit rate based on their technology type. Solar generators retire with probability 1/30 each year and wind generators retire with probability 1/25 each year. These hazards imply operating lives of 30 and 25 years, respectively, which correspond to the average lifespan of utility-scale wind and solar technology. I do not treat retirement as increasingly likely with generator age, primarily for computational reasons.²⁰

This is primarily a technical assumption. Retirement is rare in sample – only five wind generators retired over the period I study – and arrives randomly. The shortest lived wind generator in ERCOT exited after 11 years of production, for example. Wind and solar marginal costs are zero in the model; modeling strategic retirement would be challenging. The retirement rates I use are sufficiently low that retirement is unlikely for any individual generator over the time span I look at. Additionally, adding retirement into the model prevents generation from accumulating indefinitely and makes the stationary distribution of generation less reliant on the model’s initial conditions.

¹⁸In equilibrium, M must coincide with the equilibrium entry allocation across regions.

¹⁹Note that $M(g|x)$ is conditional on x , so only allocations corresponding to the same state variables are included in the same distribution.

²⁰An age-independent geometric lifetime is appealing because I do not have to keep track of generator ages.

3.4 Production

This subsection begins with a brief overview of economic dispatch on the electric grid, including key concepts about pricing and dispatch. It then proceeds by embedding these concepts within the production process for generators.

3.4.1 Economic Dispatch

Let regions be denoted by r , dispatch periods denoted by t , and renewable technology denoted by τ . Region-technology-period production is given by $q_{r\tau t}$, total regional production by $q_{rt} \equiv \sum_{\tau} q_{r\tau t}$, total cost by $C_{r\tau t}(q_{r\tau t})$, and marginal cost by $MC_{r\tau t}(q_{r\tau t}) \equiv C'_{r\tau t}(q_{r\tau t})$. Regional demand is given by D_{rt} and system demand aggregates regional demand across regions $D_t = \sum_r D_{rt}$. Let flows on transmission lines be given by $\mathcal{F}_{ct}$, with transmission line capacities of K_c .

Grid operators solve a least cost dispatch optimization problem. For a given t , they choose generation of each technology (including non-renewable technologies) at each node on the grid to minimize costs. They face three constraints: system demand equals system generation, and flows on transmission lines do not exceed transmission line capacities. Each transmission line has a positive and negative flow constraint because flows are signed in the model. Satisfying the latter two constraints requires estimating how electricity flows across transmission lines. I discuss the framework for how this works in Section 2. In Appendix B, I discuss the process I use to construct a Power Transfer Distribution Factor (PTDF) Matrix for the full grid. The PTDF matrix calculates how electricity flows across the grid as injections and withdrawals of electricity from the grid change.

The grid operator's problem can be formulated as a Lagrangian:

$$\begin{aligned} \mathcal{L}_t = & \sum_r \sum_{\tau} C_{r\tau t}(q_{r\tau t}) + \lambda_t \left(\sum_r D_{rt} - \sum_r \sum_{\tau} q_{r\tau t} \right) \\ & + \sum_c \mu_t^{c,+} \left(\sum_r PTDF_{c,r}(q_{rt} - D_{rt}) - K_c \right) \\ & + \sum_c \mu_t^{c,-} \left(- \sum_r PTDF_{c,r}(q_{rt} - D_{rt}) - K_c \right). \end{aligned} \tag{8}$$

λ_t is a Lagrangian multiplier on the system demand and $\mu_t^{c,+}$ and $\mu_t^{c,-}$ are Lagrangian multipliers on transmission constraints. $\mu_t^{c,+}$ and $\mu_t^{c,-}$ are often referred to as the shadow price of transmission capacity, indicating the value of relaxing transmission constraints by

one MW.²¹ Note that line constraints have both upper and lower limits, where sign depends on the direction in which power is flowing on the transmission line. For clarity, I omit generator production capacity limits.

Let the grid be uncongested, so $\mu_t^{c,+} = 0$ and $\mu_t^{c,-} = 0$ across all grid edges. Consider a marginal generator whose production is not at full capacity. Taking the derivative with respect to $q_{r\tau t}$ yields the system price of electricity:

$$\frac{\partial \mathcal{L}_t}{\partial q_{r\tau t}} = MC_{r\tau t}(q_{r\tau t}) - \lambda_t = 0. \quad (9)$$

Let C_t^* be the minimized system dispatch cost and $D_t \equiv \sum_r D_{rt}$. Then the price of electricity in an uncongested system is set by the marginal cost of the marginal generator. By the envelope theorem, the cost of increasing demand by one MW is λ_t :

$$\lambda_t = \frac{\partial C_t^*}{\partial D_t}. \quad (10)$$

As the grid becomes congested, μ s turn on and local prices diverge from system prices. Taking the derivative with respect to $q_{r\tau t}$ yields the price of electricity in region r :

$$\frac{\partial \mathcal{L}_t}{\partial q_{r\tau t}} = MC_{r\tau t}(q_{r\tau t}) - \lambda_t + \sum_c (\mu_t^{c,+} - \mu_t^{c,-}) PTDF_{c,r} = 0. \quad (11)$$

Rearranging gives:

$$LMP_{rt} = \frac{\partial C_t^*}{\partial D_{rt}} = \lambda_t - \sum_c (\mu_t^{c,+} - \mu_t^{c,-}) PTDF_{c,r} = MC_{r\tau t}(q_{r\tau t}). \quad (12)$$

LMP_{rt} is called the locational marginal price for a given region.

3.4.2 Generator Production

Flow payoffs depend on expected revenues. Expected revenues are given based on the solution to the dispatch model. I describe how I estimate the dispatch model in Appendix B. Simplifying (12) yields the following representation of prices:

$$LMP_{rt} = \lambda_t + \text{congestion costs}_{rt}. \quad (13)$$

²¹Congestion costs, as discussed in Section 1, are calculated as $\sum_t \sum_c [\mu_t^{c,+} F_{ct} + \mu_t^{c,-} (-F_{ct})] \delta t$, summing the shadow price of the constraint over the period of time (δt) and in the direction in which it was constrained.

Regions on the demand-side of congestion have positive congestion costs, while regions on the generation-side of congestion have negative congestion costs.

I do not include all 8,760 hours of a year in the model. Instead, I estimate dispatch for 96 hours, which are chosen and weighted based on system representativeness.²² Let ω_t denote the annual weight assigned to dispatch hour t , and let $q_{r\tau t}^*(x, g)$ denote the entrant's dispatched production. Its flow payoff is

$$\pi_{r\tau}(x, g) = \sum_t \omega_t q_{r\tau t}^*(x, g) LMP_{rt}(x, g), \quad (14)$$

Note that resource quality is embedded within $q_{r\tau t}^p$. If we let $q_{r\tau}$ indicate region-technology capacity and $f_{r\tau} \in (0, 1)$ indicate a region-technology pair's capacity factor, $q_{r\tau t}^* \leq f_{r\tau} q_{r\tau}$.

3.5 Equilibrium

A stationary equilibrium in this model yields a triple (p^*, V^*, M^*) , where p^* gives entry probabilities in each region and for each technology and x ; V^* gives the value to a generator for being on the grid in each region and for each technology and x , and M^* gives beliefs about the allocation of generation across other regions for each x . I require that:

1. Given M^* and rival policy p^* , V^* satisfies the incumbent Bellman equation,
2. Entrant values constructed from V^* generate p^* based on the logit best response,
3. Entry, retirement, and stock transitions under p^* generate a stationary allocation distribution whose conditional law is $M^*(g | x)$.

4 Data & Estimation

I compile three unique datasets to study entry empirically: an hourly production panel, which contains information on generators, including their supply curve and their location, and load, a measure of demand; a yearly infrastructure panel, which contains information on transmission lines, substations, and upgrades; and a yearly fixed cost panel, which contains information on capital costs, taxes, and other fixed cost shifters.

²²Hours differ in their level of demand, demand geography, time of year, time of day, and renewable supply. Renewable supply is based on empirical wind and solar availability data. Hours are weighted based on yearly representativeness – for example, though a high demand, low renewable supply period does not occur frequently, the revenues that generators see during these system conditions can account for a sizable portion of yearly revenues. Such an hour would be important to sample in the 96-hour sample, but would receive a low weight within that sampling.

Production Panel Using Seasonal Assessment of Resource Adequacy (SARA) and Monthly Outlook for Resource Adequacy (MORA) reports, I compile a monthly panel of generators that includes information on generator county, technology, interconnection date, and nameplate capacity. I link this panel to ERCOT Security Constrained Economic Dispatch (SCED) data at the generator level. SCED data contains the supply curves that each generator submits to the grid operator every five minutes for constrained optimization, along with the amount of electricity they sold in a period. The supply curves reveal the amount of electricity each generator is willing to sell at a given price. Load measures the volume of electricity that is demanded each hour. County-level load data for ERCOT is unavailable.

Infrastructure Panel The infrastructure panel is based on transmission line data, which comes from the Homeland Infrastructure Foundation Level Data (HIFLD). It is a database of transmission lines, ranging in voltage from 69 kV to 765 kV, available in the U.S. It contains information on the geographic location of transmission lines and the voltage of those lines. Transmission line capacity is proportional to voltage. To focus on bulk transmission of electricity, I restrict attention to ERCOT’s 230 and 345 kV transmission lines, which are ERCOT’s highest capacity lines and most frequently used for bulk transmission.²³ I link transmission line data to line-level congestion information available from ERCOT (NP6-86-CD). ERCOT’s congestion data reports, at the 5-minute level and between substation pairs, where congestion arose on the grid. It also reveals the transmission capacity in MW between the substations where the congestion happened and the shadow price of that congestion, which I describe in Section B.

I link ERCOT’s congestion data to physical grid segments via documentary review, which I describe in Appendix B.1. I use the linked dataset to identify where congestion arose at the county pair level. For the remainder of the analysis, I condense the bulk transmission kV grid in ERCOT into a graph, where counties are nodes and any transmission line that runs through two counties is treated as an edge. I assume that electricity can be stepped down from the bulk transmission grid in any county that has a transmission line running through it. In many situations, multiple transmission lines connect two counties. I recover the implied joint capacity for these transmission lines. Implicitly, I treat intracounty electricity transmission as freely available. A limited number of counties are islanded, meaning they do not have any 230 or 345 kV transmission lines. I assume generation from those counties is freely transmitted to the bulk transmission backbone in proportion to the total number of 138 kV lines that connect the islanded county to counties that lie on the transmission backbone. In total, there are 204 county nodes connected by 300 edges. 10 nodes do not

²³In two instances, I found that ERCOT described transmission lines as 345 kV lines while the HIFLD characterized them as 138 kV lines. I assumed that ERCOT’s characterization was correct in this case.

have any 230 or 345 kV transmission lines.

Fixed Cost Panel I construct a panel of yearly fixed cost shifters for both wind and solar generators. I treat capital costs, land costs, and state and federal taxes as fixed cost shifters, which are all either time- or region-varying. I cannot measure some things that clearly contribute to fixed costs, like interconnection fees or labor costs. This omitted variation is not separately identified and loads into the regional fixed-cost intercept that I estimate, described in Section 3.

I use capital costs from the Lawrence Berkeley National Laboratory 2025 wind and solar market reports (Utility-Scale Solar Update and Land-Based Wind Energy Technology Update) (Seel et al., 2025; Wiser et al., 2025). I calculate the price of land based on the Texas A&M Real Estate Research Center’s annual large-tract land price database (Texas Real Estate Research Center, 2025). I measure the Texas Chapter 313 policy tax abatement that generators were eligible to enter into with local school districts, a tax incentive for renewable generators (Texas Comptroller of Public Accounts, 2025).²⁴ I apply the Production Tax Credit (PTC) to wind generators and the Investment Tax Credit (ITC) to solar generators. The PTC applies to wind production; I annualize PTC credits to generators based on county-level wind capacity factors and sum PTC credits over a 10-year horizon. PTC credit rates varied over the 2018-2024 period: in 2018, the rate was \$0.018/kWh; in 2019, \$0.012/kWh; in 2020-2021, \$0.018/kWh; and in 2022-2024, \$0.03/kWh. The ITC is calculated as the ITC rate times the capital cost of solar projects in a given year. The ITC rate over this period was 30% in all years except 2020 and 2021, when the ITC rate was 26%.

I construct four objects with these data. First, I disaggregate load. Load data is available at the zonal level. I construct county-level load based on ERCOT’s hourly zonal load data (NP6-345-CD). I describe the process I use to construct county-level load in Appendix A.²⁵ Next, I calculate transmission line reactances based on the information in the yearly infrastructure panel. The line reactances are based on line distance and voltage. I then pair the reactance information with data on congestion and production to estimate implied transmission line capacities. I describe the process I use to estimate transmission line capacities in Appendix B.2. Finally, I estimate commitment. Each hour, generators (and sometimes the

²⁴The Chapter 313 abatement was a property tax incentive for capital investments, where investor property taxes were capped for school district Maintenance and Operations taxes purposes. Maintenance and Operations taxes vary at the school district level. The program expired at the end of 2022, though abatements negotiated before 2022 were allowed to continue until their original expiry date occurred. I generate an annual value of this program for each project with a negotiated agreement.

²⁵ERCOT allows for retail utility choice, where consumers select their utility electricity provider from several options. I account for each utility’s share of electricity deliveries in each county when I disaggregate load.

grid operator) commit to produce during that hour. Committed generators produce electricity under all load realizations, which reduces the amount of load that renewable generators must meet and changes prices. I describe this process in further detail in Appendix B.3.

4.1 Validation

Accurately capturing entry incentives on the grid requires an accurate representation of prices that entrants would see under counterfactual entry. I performed a validation exercise to assess whether the dispatch model (along with the capacity and commitment models) produce realistic prices. The exercise involved estimating the dispatch model on 2,000 hours from 2023, which were excluded from the fit of the model.

Table 3: Out-of-Sample Validation of the Dispatch Model

	Model	Observed	Bias	MAE	RMSE	Correlation
<i>Panel A: System price validation</i>						
Demand-weighted LMP (\$/MWh)	52.38	52.24	0.14	29.14	192.30	0.85
Load-shedding frequency	0.00	—	—	—	—	—
<i>Panel B: Renewable price-value validation</i>						
Solar capture price (\$/MWh)	71.89	67.67	4.22	—	—	—
Wind capture price (\$/MWh)	25.26	22.98	2.28	—	—	—
Solar revenue (\$/MW-year)	116,078	109,775	6,303	13,715	22,089	0.86
Wind revenue (\$/MW-year)	64,378	58,567	5,811	13,674	19,285	0.61

Notes: The table evaluates the dispatch model on 2,000 evenly sampled hours from 2023, which are excluded from estimation of the model. Revenue statistics are annualized by weighting each sampled hour by 8,760/2,000. The solar and wind statistics average county-level per-MW outcomes across 23 and 44 electrical county nodes, respectively. Bias is the average difference between Model and Observed outcomes. MAE is the mean average error. RMSE is sensitive to a small number of scarcity-price observations.

The model shows very strong fit at the system price and renewable price levels. Model demand-weighted LMPs in 2023 are \$52.38, while observed demand-weighted LMPs are \$52.24. The Mean Absolute Error between model and observed prices is higher – \$29.14 – though much of that discrepancy is due to tail events driving up mean. Median absolute error, for example, is \$3.89. The correlation across prices is also very high – 85%. Note that RMSE is high because of tail events, which are difficult to price accurately. Tail events are important for accurately estimating entrant revenues, as they have the potential to increase revenue dramatically. The difficulties pinning down tail revenues do not cause issues for expected wind and solar yearly per-MW revenues, which are quite accurate.

4.2 Identification

The goal of the model is to estimate region- and technology-specific entry probabilities $p_{r\tau}(x)$ as a function of the state variables. Identification of entry probabilities proceeds from equation (5), reprinted below for clarity:

$$p_{r\tau}(x) = \frac{\exp([v_{r\tau,1}(x) - F_{r\tau}]/\sigma_\tau)}{1 + \exp([v_{r\tau,1}(x) - F_{r\tau}]/\sigma_\tau)}.$$

v is the stream of earnings based on the dispatch model summed over the life of the generator. The dispatch model is pinned down by hourly and spatial variation in production and prices, which is used to estimate transmission line capacities and the commitment model. The transmission line capacities and commitment model pin down the solution to the dispatch model for the level and spatial allocation of generation on the grid.²⁶

F are the region-technology-year specific fixed costs. For a given value v , fixed costs can be computed based on the entry model. In equation (7), I embed a parameterization of fixed costs within model estimation so that I can calculate fixed costs for entrants in counterfactuals. The parameterization projects the implied fixed cost threshold from the entry model onto a series of fixed cost shifters that vary at the region, technology, and time level.

I parameterize fixed costs such that the difference between model-implied and observed entry is minimized across regions, technologies, and time. I treat observed entry as data from a binomial process:

$$n_{r\tau t} \sim \text{Binomial}(\bar{N}_{r\tau}, p_{r\tau t}(\theta_\tau, \sigma_\tau)), \quad (15)$$

where θ_τ are the non-monetary parameters of the fixed cost function and σ_τ is the scale of the cost shock that entrants receive. Then, I select θ_τ such that model fixed costs maximize the binomial likelihood of the data:

$$\hat{\theta}_\tau(\sigma) = \underset{\theta_\tau}{\operatorname{argmax}} \sum_{r,t} [n_{r\tau t} \log p_{r\tau t} + (\bar{N}_{r\tau} - n_{r\tau t}) \log(1 - p_{r\tau t})]. \quad (16)$$

I estimate this likelihood separately for solar and wind entrants. For solar entrants, the specification includes capital costs, state and federal taxes, and an intercept α_{solar} , with no other only non-cost shifters. For wind entrants, I augment the solar estimation equation

²⁶Note that I do not endogenize entry of dispatchable resources like coal and natural gas or storage. Entry probabilities are estimated on data from 2018; when simulating entry across the 2018-2024 period in counterfactuals, I compute entry probabilities based on non-renewable generation that existed on the grid in year t .

with my measure of land costs. Both solar and wind thus produce $\hat{F}_{r\tau}$, fixed costs that can be represented by shifters and fixed effects. I re-solve for equilibrium using $\hat{F}_{r\tau}$ in equation (5).

Equation (5) is additionally a function of σ , the variance of the cost shock that entrants receive. To estimate σ , I test a grid of different sigma values ranging from $\sigma = 4$ to $\sigma = 4096$. For each technology and candidate σ , I proceed as follows.

I hold out one region r . Then, using all other regions, I estimate fixed cost coefficients:

$$\hat{\theta}_{\tau,-r}(\sigma) = \underset{\theta}{\operatorname{argmax}} \sum_{j \neq r, t} \ell(n_{j\tau t}, \bar{N}_{j\tau}; p_{j\tau t}(\theta, \sigma)). \quad (17)$$

I then use the fitted fixed cost function to predict entry in r and calculate the binomial log likelihood for the held out region. Then I repeat this until every region has been held out once and add together the likelihoods. I then select the σ that maximizes the sum of the likelihoods.

4.3 Estimation

Estimating the model requires the following steps:

1. Initialize M and p ;
2. Holding M fixed, solve the $V - p$ fixed point;
3. Simulate entry and retirement based on p ;
4. Update $M(g | x)$ based on the simulated allocation of generation across regions;
5. Update V and p and repeat until policy, values, and the allocation law are stationary;
6. Project fixed costs onto shifters and choose σ that maximizes the likelihood of the data;
7. Repeat steps 2 - 5 until stationary equilibrium is reached.

I now describe how I estimate the distribution of beliefs $M(g|x)$. To make estimation computationally tractable, I discretize beliefs into three representative allocations for each state x . Each representative allocation implies a given allocation of generation g . I solve for which representative allocations should be used and how they should be weighted such that beliefs are consistent with p . $M(g|x)$ thus gives the weight that a given representative allocation has.

The simulation process works as follows. I initialize each representative allocation based on an observed allocation of generation drawn from the 2018-2024 period; in the first step of the simulation, weights are equal. Then I solve for entry: potential entrants arrive and receive a shock u_i drawn from $[0, 1]$. Entry occurs if $u_i < p_i(x)$. Some representative allocation-shock pairings add generation such that x changes, while others stay fixed. This yields a new distribution of states and allocations $x'-g'$. For each x' , I choose new representative allocations such that the chosen representative allocations minimize the distance between realized allocations and the representative allocations. The process additionally implies a new distribution of state-allocation pairs. To prevent the distribution from jumping, I dampen updates to the distribution of $x-g$ pairs such that the distribution pairs moves 25% closer to the simulated destination. Beliefs are consistent when the solved entry probabilities imply a stationary distribution of $x-g$ pairings.

It is not obvious whether multiple equilibria exist in the baseline model with a fixed transmission grid. Because the grid is fixed, as entry increases, congestion rises, prices fall, and further entry is disincentivized. Retirement of generators ensures that capacity does not continue to accumulate in any one region and reduces the model's reliance on the system's initial conditions. The spatial dependence of prices, however, makes multiple equilibria possible: for example, entry may be equally profitable in two regions but have important path dependent effects on congestion and dispatch outcomes.

5 Results

This section details the results from the dynamic entry model. I describe the estimated fixed costs $\bar{F}_{r\tau}$ and the model-implied project values $V_{r\tau}$. I then compare the model's spatial allocation of entry with observed entry and examine how annual entrant cohorts change the congestion component of prices received by incumbents.

5.1 Model Values

Estimated project costs $\bar{F}_{r\tau}$ and model-implied project values $V_{r\tau}$ are shown in Table 4. The table aggregates values across regions and across time periods. Costs and values are reported in MUSD/MW. I find that fixed costs for wind generators are almost three times larger than they are for solar generators. For both wind and solar, fixed costs fall during the period I study. For solar, this is driven by sharp capital cost decreases, while for wind it is primarily driven by tax benefits.

Fixed cost results imply average total fixed costs of \$115 MUSD for solar generators and

\$443 MUSD for wind generators. A 2023 EIA report estimated installed construction costs for solar at \$239 MUSD and wind at \$349 MUSD respectively (U.S. Energy Information Administration, 2025).²⁷ The fixed cost parameterization anchors both technologies to net capital costs. Wind fixed costs additionally vary with the regional land-cost proxy, while solar fixed costs include only the net-capital-cost anchor and an intercept.

Table 4: Estimated Project Costs and Dynamic Project Values

	Solar	Wind
<i>$\bar{F}_{r\tau}$, estimated project costs</i>		
Mean $\bar{F}_{r\tau}$	0.78	2.21
p10 $\bar{F}_{r\tau}$	0.62	1.56
p90 $\bar{F}_{r\tau}$	1.13	2.93
<i>$V_{r\tau}$, model-implied project values</i>		
Mean $V_{r\tau}$	0.46	0.63
Region-year SD of $V_{r\tau}$	0.07	0.14
p10 $V_{r\tau}$	0.36	0.45
p90 $V_{r\tau}$	0.54	0.82
Mean congestion discount (percent)	1.3	3.8
Region-year SD of congestion discount (p.p.)	2.1	5.8

Notes: All monetary entries are reported in MUSD/MW and are evaluated over observed 2018–2024 regional states. Statistics weight region-year cells equally. The congestion discount is the percent reduction in project value under local rather than system prices.

Table 4 also reports implied $V_{r\tau}$ for wind and solar. I find that mean $V_{r\tau}$ is lower than fixed costs for wind and solar, consistent with entry rates of 11.3% and 14.4% respectively. Mean $V_{r\tau}$ is roughly two-thirds the size of average fixed costs for solar and one-third the size of fixed costs for wind. Project values for wind are higher than they are for solar. Intuitively, $V_{r\tau}$ depends on (and increases in) the amount of electricity that a generator produces over its lifetime and the price it receives for that electricity. Wind generators have higher capacity factors (a measure how much electricity a generator can produce relative to its capacity) than solar generators do, which drives the observed differences in $V_{r\tau}$. This is true even though wind generators face lower prices than solar generators do: on average, LMPs for wind generators are 3.8% below the system price of electricity, whereas they are only 1.3% below the system price for solar generators.²⁸ The discount faced by wind generators varies dramatically; in one region (Willacy county, in the far south of Texas), average congestion discounts faced by entrants are 14.9%.

²⁷Seel et al. (2024) and Wiser et al. (2024) estimate similar fixed costs for wind and solar.

²⁸All results in Table 4 are conditional on entry.

Figure 4 assesses the spatial fit of the dynamic entry model. Each point in the figure represents a model region. The x-axis shows observed cumulative entry in representative-project equivalents for each region between 2018 and 2024, and the y-axis shows corresponding model-implied cumulative entry.²⁹ The correlation between model and observed entry is 0.81 for solar and 0.91 for wind. A line of best fit has slope 0.34 for solar and 0.64 for wind. The model compresses the spatial distribution towards the mean for both wind and solar.

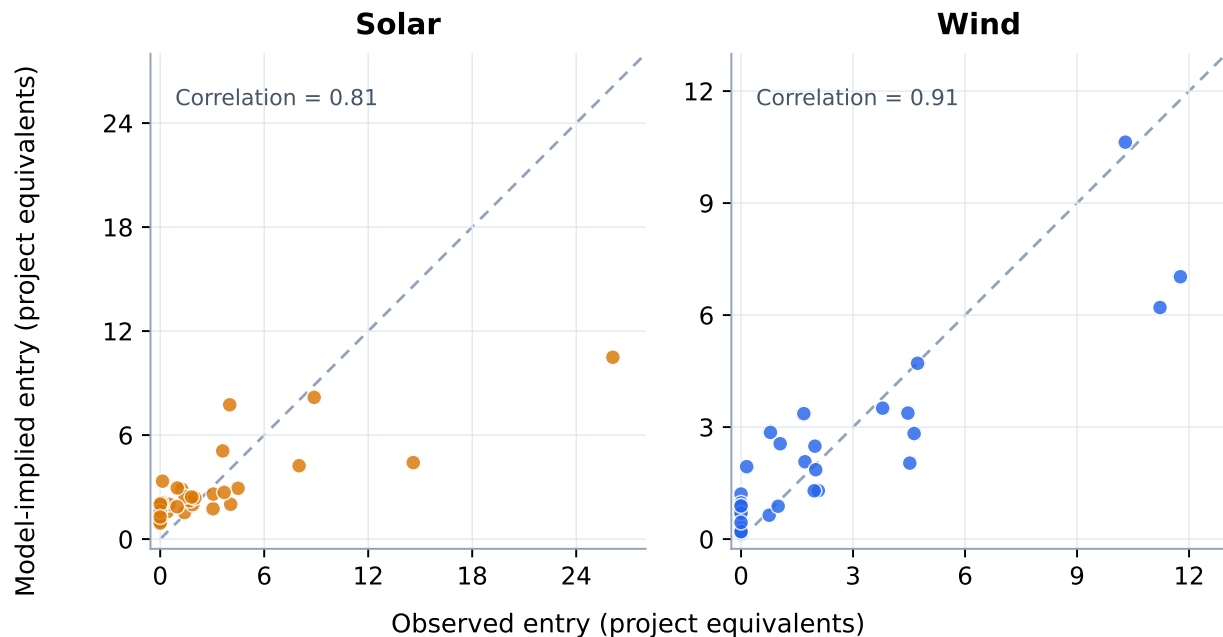


Figure 4: Observed and Model-Implied Cumulative Regional Entry, 2018–2024

Notes: Each point is a model region. The dashed line is the 45-degree line.

There are several points where observed wind and solar entry is higher than model-predicted wind and solar entry. The far west is difficult for solar to pin down correctly: in the data, 26.1 solar generators entered the far west, while the model predicts only 10.5 generators enter in that region. One potential reason for this comes from Table 7: the far west is where demand grew most dramatically over this period, and thus where one might expect the stationary demand assumption to be more problematic. Other regional misses are less symptomatic: wind generator entry is too low in the eastern plains of Texas; solar entry is too low in west-central Texas.

²⁹Including an intercept in the fixed effect parameterization mechanically recovers entry in the aggregate.

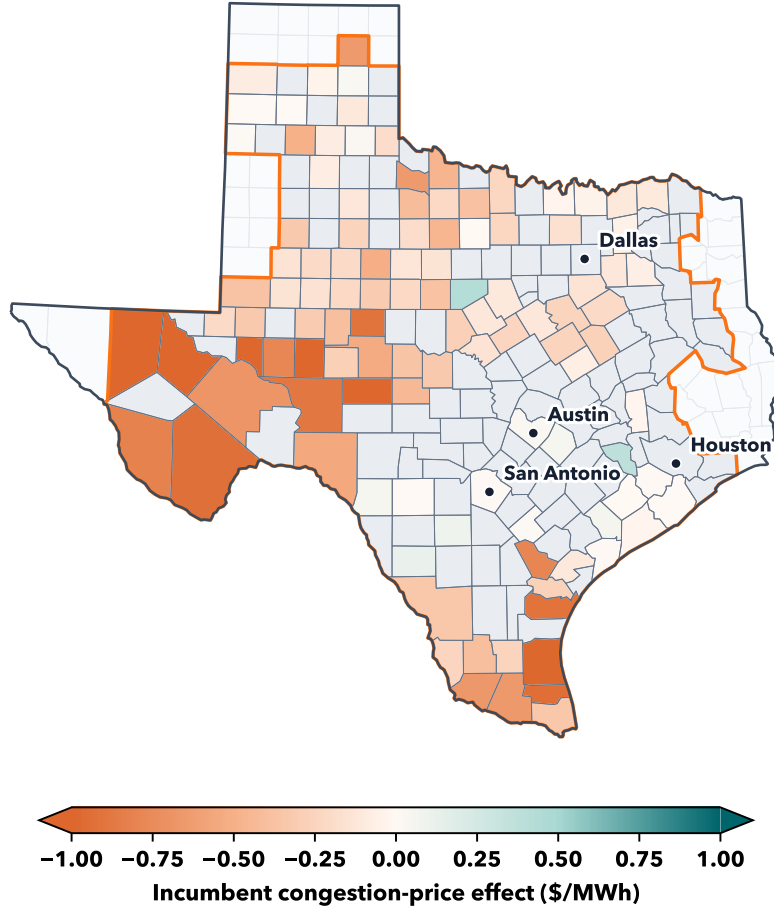


Figure 5: County-level incumbent congestion-price effects of annual renewable entry, 2018–2024

Notes: Each paired dispatch adds the year’s new wind and solar sites to an otherwise fixed grid and demand environment. For each county-hour, the effect is no-entry incumbent generation times the change in county price relative to the Harris reference-node price. The county mean divides the summed effect by no-entry incumbent MWh. Orange denotes a lower relative price; teal denotes a higher relative price. Gray ERCOT counties have no modeled renewable incumbent generation.

The motivating example for the entry model (Section 2) identified two potential inefficiencies in the generator entry problem. The second inefficiency, the coordination failure, needs counterfactual analysis to assess. The first inefficiency, loop flows, is visible from the entry model. Figure 5 calculates, for each region-year-hour combination, how entry shifts the congestion costs that incumbents face when they produce. The calculation fixes incumbent generation at the level they would produce without any entry. Then it asks how congestion costs shift in the incumbent’s region when entry occurs across the grid. Reported values average incumbent price penalties across all years in the data.

The results suggest that loop flows are most costly for generators in the highest resource

quality regions: the far west and south Texas. Interestingly, loop flows are less costly in the panhandle, possibly reflecting the already-low GW of generation in the region. Loop flows immediately outside of population centers, on the other hand, are zero or sometimes positive, reflecting that entry causes congestion, which raises prices in counties that are downstream of the congestion.

6 Counterfactuals

The entry model illustrates that congestion shifts generator entry decisions. It remains unclear how costly the lack of coordination between generation and transmission is. In a counterfactual exercise, I test two different infrastructure provision policies, each designed to target the coordination inefficiency. To understand entry behavior under each policy, I implement the policy and then compute equilibrium entry policies using the entry model. I make several adjustments to the entry model to incorporate the effect of long-lived infrastructure investments, which I describe in Section 6.1. Then, using the new equilibrium entry policies, I assess how the Texas grid would have developed had the different entry policy been implemented from 2018 - 2024. I simulate 200 growth paths for the grid under each infrastructure policy.³⁰ My outcome of interest is social welfare, which I calculate as:

$$W_k = -\mathbb{E}_k \left[\sum_{h \in \mathcal{H}} \omega_h \left\{ \sum_r \sum_{\tau} C_{r\tau h}(q_{r\tau h k}) + \chi e_{hk} \right\} + a_G \sum_{i \in \mathcal{G}_k} F_i + a_T K(\Delta Z_k) \right]. \quad (18)$$

Here, h indexes hour of the year, k indexes the policy, e_{hk} denotes carbon dioxide emissions, and χ is the social cost of carbon. $\mathcal{G}_k$ is the set of projects that enter under policy k , and F_i is project i 's fixed cost from the model. $K(\Delta Z_k)$ is the cost of transmission construction. a_G and a_T are the annualization factors for generation and transmission investment, respectively. Roughly, welfare depends on three objects: production costs (generation, emissions); new entrant fixed costs; and transmission costs. Note that demand is not included in welfare because it remains fixed across policies.

The first policy, which I call the upgrade-on-entry policy, adapts an entry policy used in much of the rest of the U.S. to the Texas grid.³¹ In it, grid operators add an intermediate stage between generators entering and production. In this stage, grid operators run the

³⁰I use the same shocks across infrastructure policies, so the only thing that varies across each counterfactual is the implemented infrastructure policy.

³¹The policy is often called “invest-and-connect,” whereas the Texas policy is called “connect-and-manage.” Invest-and-connect policies famously lead to long wait times in interconnection queues, see Johnston et al. (2024), an issue I do not consider in this paper.

dispatch model over three different planning hours for the entrants. The hours are chosen to mimic high system-stress conditions – I use data from an hour in the summer peak demand period, an hour in the winter peak demand period, and an hour where demand is low relative to generation availability. If the entering generator causes congestion in those hours, then they are required to pay entry fees to provide the least-cost upgrade to the grid that prevents congestion from arising. The entry fees are split in proportion to the amount of the congestion that they cause on each line. Entrants anticipate the fees, though they face uncertainty about how costly the fee they face will be due to other entrants (in their region and other regions) simultaneously making entry decisions. This policy forces generators to internalize the cost that their entry imposes on the grid and allows them to choose locations with minimal congestion risk. Because entry is forward-looking, entrants under the upgrade-on-entry policy account for the dynamic free-riding effect the policy induces, where new upgrades shift future entry decisions.

Next, I consider a market for new transmission. This policy is similar to “open season” policies used for new pipeline development; Kavulla (2026) calls for implementing a similar idea in response to data center demand. Under this policy, grid operators add an intermediate stage between generators entering and production. In this stage, entrants, incumbents, and load all submit bid curves to the grid operator, revealing their willingness-to-pay for new transmission. The grid operator then selects the upgrade (or set of upgrades) that maximizes willingness-to-pay minus upgrade costs.³² This policy targets the coordination inefficiency directly: agents internalize both the benefits and costs of new transmission in proportion to their use of that transmission. Similar to upgrade-on-entry, bidders consider the dynamic effects of new transmission when forming their bid curves.

6.1 Model Additions

The counterfactuals require two additions to the model: a method for selecting upgrades and state variables that contain information about grid capacity. I discuss each of them in turn.

There are 300 corridors in the dispatch model, each of which is eligible for an upgrade. I treat upgrades as a flat 1200MW capacity addition to a corridor. There are significant complementarities across upgrades. For example, if a rural, high-wind region is connected to demand by a single transmission line that has two corridors, upgrading one of those corridors does not improve the grid. Congestion still arises on the unupgraded corridor. Instead, properly evaluating the value of an upgrade requires evaluating the effect of upgrading both

³²Bids are constrained to be positive. I assume bids are honest and accurate; designing an incentive-compatible auction for new transmission is a future direction of research.

links at the same time.

To do so, I proceed with a beam search through upgrade packages (Meister et al., 2020). Beam search, which comes from computer science, is a graph and tree search algorithm that focuses on searching near high-value nodes. For example, consider a network with four corridors: A, B, C , and D . A beam search begins by evaluating an upgrade on each individual corridor. It then identifies the W top upgrades and moves on to the next level of evaluation. Consider for example, $W = 2$, where A and C survive. Then the search evaluates upgrade pairings AB, AC, AD, BC, CD , but not BD . The search continues moving through levels until potential upgrade groups are exhausted.³³

For the purposes of the counterfactual, only corridors with congestion or corridors which reduce congestion elsewhere following an upgrade are included in the beam search. Any corridor upgrade that only becomes valuable conditional on another upgrade occurring and that also is not originally congested will not be included in the search. Assessing a corridor in the beam search involves applying a 1200MW capacity addition to the corridor, re-computing the PTDF matrix, and seeing how electricity flows adjust to determine whether the upgrade changes congestion on the grid. The width W of the search at each level is 100.

The upgrades chosen in equilibrium shift congestion and therefore prices. Including the grid as a state would be computationally infeasible. Instead, I model generators as caring about upgrades insofar as they change local prices, curtailment, and profits. This effectively treats the grid as a hidden state, similar to the way that entrants take other-region entry into consideration. As a result, counterfactual beliefs $M(g, Z|x)$ are formed over the spatial allocation of entry g and the capacity of the grid Z . I solve for beliefs using forward simulation, as in Section 3.2.1.

I model stationary beliefs over g and Z . Grid upgrades persist indefinitely. The stationary assumption implies that the grid reaches a point where upgrades will no longer be economical. This reflects the fact that generators do not expect changes to fixed costs (though they are realized in the counterfactual simulation exercise) or demand (which is fixed in the counterfactual simulation exercise). Instead, new entry is driven by retirement and grid upgrades. Beliefs, then, are stationary when further upgrades are no longer made in expectation for a given state.

In the upgrade-on-entry counterfactual, entry proceeds in two steps. First, entrants apply to enter the grid. Entrants apply if the value of applying is greater than the fixed cost of building a renewable generator and the expected entry fee they will face upon entering. The entry fee depends on the size and location of the entering cohort and the congestion patterns

³³Note that BD is never evaluated in this example; exhausting potential upgrade pairings mean all pairings which include either A or C . All three- and four-level groups including A and C would be evaluated.

that cohort will induce once they join the grid. In the second step, entrants receive their entry fee. Fixed costs are not sunk at this point, so entrants can freely withdraw from the grid. They enter if the value of entering is greater than the fixed cost of building a renewable generator and the entry fee they have been allocated.

In the market for transmission counterfactual, entry and upgrades happen simultaneously. Because participation in the market is optional, entrants do not face any additional fees upon entering. Instead, each period all generators gain the option of submitting a bid curve to the grid operator. Because generators only consider the effect of upgrades on prices, curtailment, and profits, they do not submit bids for individual upgrades. Instead, they use beliefs about upgrade packages to submit bids over the value of future upgrades, weighted by the likelihood of those upgrades occurring. Bids are indexed by the increase in deliverability that an upgrade would give a generator and the value that incremental upgrade would represent. Intuitively, generators project what the value of their generator would be if upgrades were constructed such that they achieved a given deliverability level. The deliverability-value bid that a generator submits is the simple average value they get across all upgrade scenarios that result in the generator achieving that deliverability level.

I do not consider load as a strategic actor in the auction. Instead, I assume that the grid operator receives perfect information about the value of a grid upgrade to load, where value is represented by the change in price for load multiplied by the volume of consumers receiving that change in price. The grid operator then chooses the grid upgrade package which maximizes willingness-to-pay for generators and load, less the costs of constructing new transmission.

6.2 Results

Table 5 shows the results of the counterfactual analysis. The results show how transmission upgrades, renewable entry, dispatch emissions, welfare, and prices change under each infrastructure policy during the 2018 – 2024 period.

On average, the Upgrade-on-Entry policy leads to over 9 corridor upgrades. Despite the increased transmission availability, renewable entry drops precipitously relative to the Texas baseline. By the end of the period, there is almost 3 GW less solar on the grid and over 1 GW less wind on the grid. While increased transmission availability reduces congestion on the grid, emissions rise under Upgrade-on-Entry relative to baseline. As a consequence, welfare is much lower than it is in the baseline, costing agents over \$2.6 billion over the period. Finally, due to the increased use of costly natural gas and coal, prices increase over the baseline.

The Market counterfactual leads to a similar number of upgrades as the Upgrade-on-Entry policy with more renewable entry. Whereas assessing entry fees causes significant exit relative to the Texas baseline, the market for transmission induces roughly 5% less entry than the Texas baseline. The market induces less entry because, with more transmission availability, there is less congestion. This lowers prices near demand centers, which in turn reduces renewable entry in those locations. The reduced renewable entry, however, leads to more emissions as more natural gas is used in equilibrium. Welfare decreases slightly, primarily due to increased carbon emissions.

Table 5: Historical Replay Outcomes, 2018–2024

	Baseline	Upgrade-on-Entry	Market
Upgrades	0.00	9.72	9.13
Renewable entry (MW)	32,208	27,711	30,627
Emissions (Mt CO ₂)	981.90	1,004.59	986.83
Welfare change vs. baseline (\$M PV)	0	−2,656	−643
Demand-weighted price (\$/MWh)	18.72	19.23	18.65

Notes: Outcomes are averaged over 200 simulated paths per policy. Upgrades, entry, and emissions are cumulative from 2018 through 2024. Welfare is the discounted present value of annual welfare from Equation 18, including entrants’ taste surplus, using a discount factor of 0.92 and a social cost of carbon of \$184/t (2018 dollars). The demand-weighted price is the 2018–2024 mean of annual average LMPs, weighting each region by its share of system demand. Market results are pending.

Alternative infrastructure policies have different effects on wind and solar. In table 6, I show the average fees that each technology pays upon entering under each policy. Under upgrade-on-entry, solar entrants pay \$2.94 million and wind entrants pay \$7.59 million. This difference reflects the geographical constraints each technology faces: wind entrants have less flexibility to enter in areas with sufficient transmission capacity, while solar entrants can enter in locations just outside of demand centers and take advantage of existing transmission capacity. The Market results indicate the importance of loop flows for driving latent demand for transmission: incumbents and entrants pay roughly equal shares of new transmission costs. Entrants on the other hand pay only a small share of total transmission costs. Consistent with transmission-driven cost decreases, load is willing to pay hundreds of millions of dollars for the transmission investments chosen in equilibrium.

Figure 6 shows how entry under the Upgrade-on-Entry counterfactual differs from baseline entry. I find that imposing costs on entrants inadvertently exacerbates the coordination inefficiency: entrants located far from load face expensive upgrade bills, while entrants nearby to load can freeride on upgrades after they happen. This shifts the spatial allocation of gen-

Table 6: Payments for Transmission Upgrades, 2018–2024

	Payment (\$M)	Basis
<i>Upgrade-on-Entry</i>		
Solar entrant	2.94	per project
Wind entrant	7.59	per project
<i>Market: cumulative 2018–2024 payments</i>		
Entrants	25.28	per path
Incumbent renewables	208.57	per path
Load	617.07	per path

Notes: The Upgrade-on-Entry row reports total payments divided by the number of connected projects across all simulated paths and years. The average includes connected projects that pay no upgrade fee. Market results are pending.

eration closer to the East. The effect is most pronounced for solar generation, which loses almost 2 GW of generation in the west and adds generation in the east. Wind effects are more muted, though several regions in central and west Texas lose up to 200 MW of wind production. A small amount of wind relocates in east Texas, where wind resources are worse.

Whereas both the Texas baseline and the Upgrade-on-Entry policies locate renewable generation in the east, the Market counterfactual pushes entry towards high resource quality areas in central and west Texas. It additionally selects a higher proportion of wind generation, taking advantage of Texas’ natural wind resources.

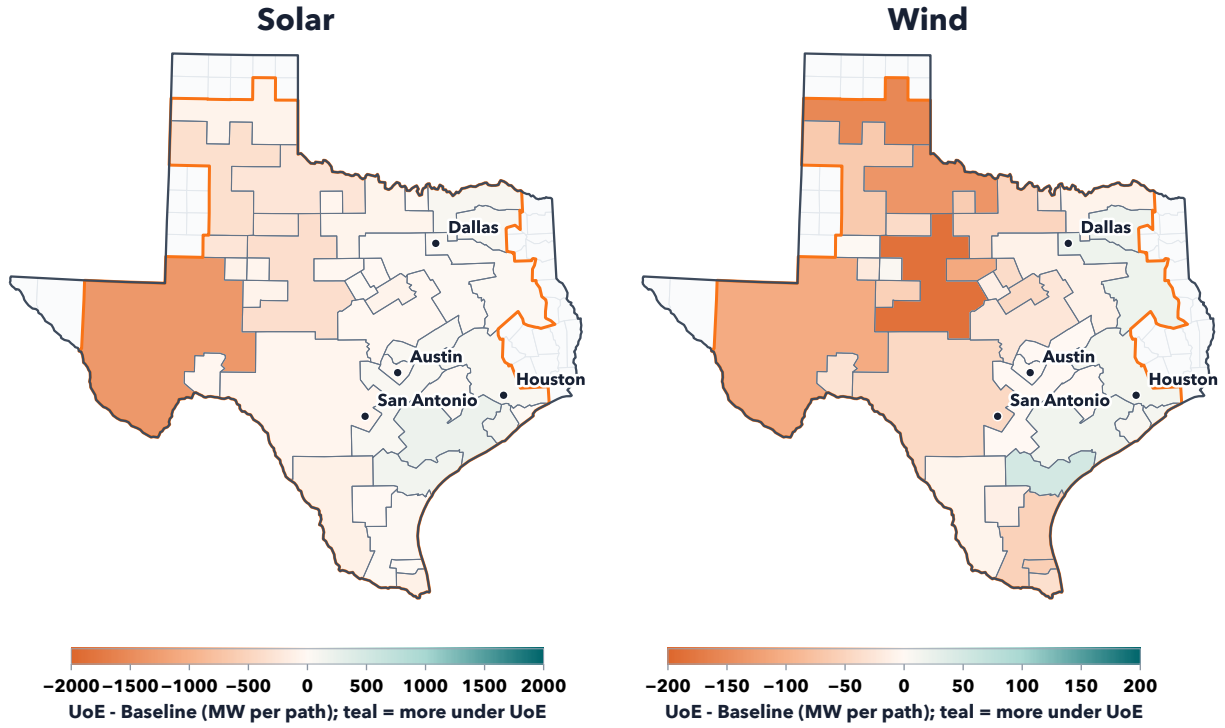


Figure 6: Cumulative renewable entry by region, 2018–2024: Upgrade-on-Entry minus baseline

Notes: Each region shows cumulative 2018–2024 entry under Upgrade-on-Entry minus cumulative entry under the baseline, in MW per simulated path. Teal regions receive more entry under Upgrade-on-Entry; orange regions receive more entry under the baseline. Color scales differ across panels. The orange line marks the ERCOT boundary; counties outside it are shaded white. Regions are clipped to the ERCOT footprint, as in Figure 5. Points mark the four largest load centers.

7 Conclusion

Researchers have increasingly begun to investigate what the value of new transmission is and what competitive effects it might have. In this paper, I investigate how resource quality and transmission availability determine renewable generator entry decisions. I am able to capture the network structure of prices on the electric grid, endogenizing congestion and profits for generators that vary based on location and technology type. The detailed network structure of my data gives me particular insight into how entry in one region can affect prices in many other regions, and what that entry reveals about demand for transmission among generators.

One focus of my paper is understanding how different transmission provision policies shift entry behavior. I start by comparing the baseline policy in ERCOT – which I characterize as a fixed grid policy – to the main policy used elsewhere in the U.S. – upgrade-on-entry, where entrants make upgrades to avoid causing congestion on the grid. I find ERCOT’s baseline policy greatly outperforms the upgrade-on-entry policy. By forcing entrants to upgrade the grid, the policy leads to entry where transmission is plentiful, even if sun and wind availability is low in the area. This is costly for the grid. Next, I consider implementing a market for transmission. I find that this performs roughly as well as the ERCOT baseline policy. It constructs more transmission however and leads to a higher proportion of entry in regions with good quality renewable resources.

The results from the market counterfactual are of particular interest given the situation the grid finds itself in currently. Electricity demand in ERCOT is projected to triple by 2030. The location of new demand depends on idiosyncratic factors like latency, land costs, and water availability. One particular appeal of the market policy for new transmission is that it can respond to this growing demand in optimal ways – letting users of the grid determine the value of more transmission will lead to a more efficient build-out of the grid than relying on centralized planning and entry payments that correspond to projected congestion causation.

This paper is also of interest to infrastructure development more broadly. As I show in Section 2, congestible networks have difficult-to-predict interactions with entry incentives. Entry model results suggest that separately solving for entry and infrastructure provision leads to distorted entry decisions. The distorted entry decisions, in turn, reduce the value of new transmission, pushing markets into suboptimal equilibria. I show that infrastructure developers should attempt to jointly solve for entry and infrastructure provision.

References

- American Electric Power (2008). “Transmission Facts.” URL https://web.ecs.baylor.edu/faculty/grady/_13_EE392J_2_Spring11_AEP_Transmission_Facts.pdf.
- Arkolakis, Costas and Conor Walsh (2023). “Clean Growth.” *Working Paper*, URL <https://static1.squarespace.com/static/5b4b997eda02bc592b5131cd/t/64e38ceeb5dae75b3b9cb7e3/1692634362860/CleanGrowth.pdf>.
- Boatwright, Abigail (2025). “Transmission Congestion is Knocking the Wind Out of Renewable Investments.” *Working Paper*.
- Borenstein, Severin, James Bushnell and Steven Stoft (2000). “The Competitive Effects of Transmission Capacity in a Deregulated Electricity Industry.” *RAND Journal of Economics*, 31(2): 294–325, URL <https://www.jstor.org/stable/2601042>.
- Brancaccio, Giulia, Myrto Kalouptsi and Theodore Papageorgiou (2024). “Investment in Infrastructure and Trade: The Case of Ports.” Working Paper 32503, National Bureau of Economic Research, URL <https://doi.org/10.3386/w32503>.
- Chao, Hung-po and Stephen Peck (1996). “A Market Mechanism for Electric Power Transmission.” *Journal of Regulatory Economics*, 10(1): 25–59, URL <https://doi.org/10.1007/BF00133357>.
- Chen, Luming (2025). “The Dynamic Efficiency of Policy Uncertainty: Evidence from the Wind Industry.” Working paper, University of Michigan, URL <https://doi.org/10.2139/ssrn.5346248>.
- Cohn, Julie A. (2022). “Connecting Past and Future: A History of Texas’ Isolated Power Grid.” Research Paper 12.01.22, Center for Energy Studies, Rice University’s Baker Institute for Public Policy, URL <https://www.bakerinstitute.org/research/connecting-past-and-future-history-texas-isolated-power-grid>.
- Congressional Budget Office (2026). “Overview of Electric Transmission.” URL <https://www.cbo.gov/publication/62705>, presentation published August 27, 2026.
- De Cannière, Charlotte (2026). “Market Integration and Market Efficiency: Evidence from Transmission Constraints in the Belgian Electricity Sector.” *Working Paper*, URL <https://drive.google.com/file/d/11ThfDoWiZRIfd-G1dhqwULZrVOC6BoUC/view>.
- Desmet, Klaus and Esteban Rossi-Hansberg (2014). “Spatial Development.” *American Economic Review*, 104(4): 1211–1243, URL <https://doi.org/10.1257/aer.104.4.1211>.

- Dunlop, R. D., R. Gutman and P. P. Marchenko (1979). “Analytical Development of Loadability Characteristics for EHV and UHV Transmission Lines.” *IEEE Transactions on Power Apparatus and Systems*, PAS-98(2).
- Duranton, Gilles and Matthew A. Turner (2011). “The Fundamental Law of Road Congestion: Evidence from US Cities.” *American Economic Review*, 101(6): 2616–2652, URL <https://doi.org/10.1257/aer.101.6.2616>.
- Electric Reliability Council of Texas (2022). “ERCOT Nodal Protocols.” Protocols, Electric Reliability Council of Texas, URL <https://www.ercot.com/files/docs/2022/10/11/July%2015%2C%202022%20Nodal%20Protocols.pdf>.
- Electric Reliability Council of Texas (2025). “Fuel Mix Report: 2007–2024.” URL https://www.ercot.com/files/docs/2021/03/10/FuelMixReport_PreviousYears.zip, fuel mix reports for 2007–2024.
- Electric Reliability Council of Texas (2026). “About ERCOT.” URL <https://www.ercot.com/about>, accessed August 27, 2026.
- Ericson, Richard and Ariel Pakes (1995). “Markov-Perfect Industry Dynamics: A Framework for Empirical Work.” *The Review of Economic Studies*, 62(1): 53–82, URL <https://doi.org/10.2307/2297841>.
- Fell, Harrison, Daniel T. Kaffine and Kevin Novan (2021). “Emissions, Transmission, and the Environmental Value of Renewable Energy.” *American Economic Journal: Economic Policy*, 13(2): 241–272, URL <https://www.aeaweb.org/articles?id=10.1257/pol.20190258>.
- Fernald, John G. (1999). “Roads to Prosperity? Assessing the Link between Public Capital and Productivity.” *American Economic Review*, 89(3): 619–638, URL <https://doi.org/10.1257/aer.89.3.619>.
- Golden, Dana (2026). “Investment and the Transfer of Power: Dynamic Effects of Transmission in Electricity Markets.” *Working Paper*, URL [https://jgolden36.github.io/files/JMP%20\(11\).pdf](https://jgolden36.github.io/files/JMP%20(11).pdf).
- Gonzales, Luis E., Koichiro Ito and Mar Reguant (2023). “The Investment Effects of Market Integration: Evidence from Renewable Energy Expansion in Chile.” *Econometrica*, 91(5): 1659–1693, URL https://koichiroito.com/pdfs/Market_Integration_Gonzales_Ito_Reguant.pdf.

- Gowrisankaran, Gautam, Stanley S. Reynolds and Mario Samano (2016). “Intermittency and the Value of Renewable Energy.” *Journal of Political Economy*, 124(4): 1187–1234, URL https://www.nber.org/system/files/working_papers/w17086/revisions/w17086.rev2.pdf.
- Hausman, Catherine (2024). “Power Flows: Transmission Lines, Allocative Efficiency, and Corporate Profits.” *American Economic Review*, URL <https://www.nber.org/papers/w32091>.
- Hogan, William, Juan Rosellón and Ingo Vogelsang (2010). “Toward a Combined Merchant-Regulatory Mechanism for Electricity Transmission Expansion.” *Journal of Regulatory Economics*, 38: 113–143, URL <https://link.springer.com/article/10.1007/s11149-010-9123-2>.
- Holland, Stephen P., Erin T. Mansur and Andrew J. Yates (2024). “Electrification in the Long Run.” *Working Paper*, URL https://mansur.host.dartmouth.edu/papers/holland_mansur_yates_longrun.pdf.
- Hörsch, Jonas, Fabian Hofmann, David Schlachtberger and Tom Brown (2018). “PyPSA-Eur: An Open Optimisation Model of the European Transmission System.” *Energy Strategy Reviews*, 22: 207–215, URL <https://doi.org/10.1016/j.esr.2018.08.012>.
- Ifrach, Bar and Gabriel Y. Weintraub (2017). “A Framework for Dynamic Oligopoly in Concentrated Industries.” *Review of Economic Studies*, 84(3): 1106–1150, URL <https://doi.org/10.1093/restud/rdw047>.
- Jankovska, Olivera and Julie A. Cohn (2020). “Texas CREZ Lines: How Stakeholders Shape Major Energy Infrastructure Projects.” Research paper, Rice University’s Baker Institute for Public Policy, URL <https://www.bakerinstitute.org/research/texas-crez-lines-how-stakeholders-shape-major-energy-infrastructure-projects>.
- Jia, Panle (2008). “What Happens When Wal-Mart Comes to Town: An Empirical Analysis of the Discount Retailing Industry.” *Econometrica*, 76(6): 1263–1316, URL <https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA6649>.
- Johnston, Sarah, Yifei Liu and Chenyu Yang (2024). “An Empirical Analysis of the Interconnection Queue.” *Working Paper*, URL https://econ-chenyu-yang.github.io/interconnection_queues.pdf.

- Joskow, Paul and Jean Tirole (2005). “Merchant Transmission Investment.” *Journal of Industrial Economics*, 53(2): 233–264, URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.0022-1821.2005.00253.x>.
- Kavulla, Travis (2026). “How Will Data Centers Pay for Power?” *American Affairs*, X(2), URL <https://americanaffairsjournal.org/2026/05/how-will-data-centers-pay-for-power/#notes>.
- Krugman, Paul (1991). “Increasing Returns and Economic Geography.” *Journal of Political Economy*, 99(3): 483–499, URL <https://doi.org/10.1086/261763>.
- Krugman, Paul and Anthony J. Venables (1995). “Globalization and the Inequality of Nations.” *The Quarterly Journal of Economics*, 110(4): 857–880, URL <https://doi.org/10.2307/2946642>.
- Kundur, Prabha (1994). *Power System Stability and Control*. McGraw-Hill, New York.
- Léautier, Thomas-Olivier (2000). “Regulation of an Electric Power Transmission Company.” *The Energy Journal*, 21(4): 61–92, URL <https://www.jstor.org/stable/41322900>.
- Mays, Jacob (2023). “Generator Interconnection, Network Expansion, and Energy Transition.” *IEEE Transactions on Energy Markets, Policy and Regulation*, 1(4): 410–419, URL <https://ieeexplore.ieee.org/document/10121623>.
- Medjroubi, Wided, Ulf Philipp Müller, Malte Scharf, Carsten Matke and David Kleinhans (2017). “Open Data in Power Grid Modelling: New Approaches Towards Transparent Grid Models.” *Energy Reports*, 3: 14–21, URL <https://doi.org/10.1016/j.egyr.2016.12.001>.
- Meister, Clara, Tim Vieira and Ryan Cotterell (2020). “Best-First Beam Search.” *Transactions of the Association for Computational Linguistics*, 8: 795–809, URL https://doi.org/10.1162/tac1_a_00346.
- North American Electric Reliability Corporation (). “FAC-008-5: Facility Ratings.” URL <https://www.nerc.com/pa/Stand/Reliability%20Standards/FAC-008-5.pdf>.
- Pozo, David, Javier Contreras and Enzo Sauma (2013). “If You Build It, He Will Come: Anticipative Power Transmission Planning.” *Energy Economics*, 36: 135–146, URL <https://doi.org/10.1016/j.eneco.2012.12.007>.

- Redding, Stephen J. and Esteban Rossi-Hansberg (2017). “Quantitative Spatial Economics.” *Annual Review of Economics*, 9: 21–58, URL <https://doi.org/10.1146/annurev-economics-063016-103713>.
- Rivera, Jose, Pezhman Nasirifard, Johannes Leimhofer and Hans-Arno Jacobsen (2019). “Automatic Generation of Real Power Transmission Grid Models From Crowdsourced Data.” *IEEE Transactions on Smart Grid*, 10(5): 5436–5448, URL <https://doi.org/10.1109/TSG.2018.2882840>.
- Seel, Joachim, Julie Mulvaney Kemp, Anna Cheyette, Will Gorman, Naïm R. Darghouth, Dana Robson, Joseph Rand and Seongeun Jeong (2025). “U.S. Utility-Scale Solar, 2025 Data Update.” Technical report, Lawrence Berkeley National Laboratory, URL <https://emp.lbl.gov/research-areas/utility-scale-solar>.
- Seel, Joachim, Julie Mulvaney Kemp, Anna Cheyette, Dev Millstein, Will Gorman, Seongeun Jeong, Dana Robson, Rachman Setiawan and Mark Bolinger (2024). “Utility-Scale Solar, 2024 Edition: Empirical Trends in Deployment, Technology, Cost, Performance, PPA Pricing, and Value in the United States.” Technical report, Lawrence Berkeley National Laboratory, URL <https://emp.lbl.gov/publications/utility-scale-solar-2024-edition>.
- Seim, Katja (2006). “An Empirical Model of Firm Entry with Endogenous Product-Type Choices.” *RAND Journal of Economics*, 37(3): 619–640, URL <https://pages.stern.nyu.edu/~acollard/seim.pdf>.
- Shreve, Nathan, Julia Selker, Zach Zimmerman and Richard Doying (2025). “Transmission Congestion for 2024.” Report prepared for the connected grid initiative, Grid Strategies LLC, URL https://gridstrategiesllc.com/wp-content/uploads/GS_Transmission-Congestion-for-2024.pdf.
- Stott, Brian, Jorge Jardim and Ongun Alsac (2009). “DC Power Flow Revisited.” *IEEE Transactions on Power Systems*, 24(3): 1290–1300, URL <https://doi.org/10.1109/TPWRS.2009.2021235>.
- Sweeting, Andrew (2013). “Dynamic Product Positioning in Differentiated Product Markets: The Effect of Fees for Musical Performance Rights on the Commercial Radio Industry.” *Econometrica*, 81(5): 1763–1803, URL <https://doi.org/10.3982/ECTA9856>.
- Texas Comptroller of Public Accounts (2025). “Report of the Texas Economic Development

- Act.” Technical report, URL <https://comptroller.texas.gov/economy/development/prop-tax/ch313/reports/96-1359-2025.php>.
- Texas Real Estate Research Center (2025). “Texas Rural Land Markets.” URL <https://trerc.tamu.edu/texas-rural-land-markets/>.
- Trabish, Herman K. (2025). “Will ERCOT’s Streamlined Connect-and-Manage Approach Work for Other Markets?” *Utility Dive*, URL <https://www.utilitydive.com/news/ercot-connect-and-manage-spp-miso-eris/749083/>.
- U.S. Energy Information Administration (2025). “Construction Cost Data for Electric Generators Installed in 2023.” URL <https://www.eia.gov/electricity/generatorcosts/archive/2023/>, data collected on Form EIA-860, Annual Electric Generator Report.
- U.S. Energy Information Administration (2026). “Form EIA-860 Detailed Data with Previous Form Data (EIA-860A/860B).” URL <https://www.eia.gov/electricity/data/eia860/>, form EIA-860 detailed data, including historical EIA-860A and EIA-860B files and the 2025 early release.
- Venables, Anthony J. (1996). “Equilibrium Locations of Vertically Linked Industries.” *International Economic Review*, 37(2): 341–359, URL <https://doi.org/10.2307/2527327>.
- Vogelsang, Ingo (2001). “Price Regulation for Independent Transmission Companies.” *Journal of Regulatory Economics*, 20: 141–165, URL <https://link.springer.com/article/10.1023/A:1011103328722>.
- Weintraub, Gabriel Y., C. Lanier Benkard and Benjamin Van Roy (2008). “Markov Perfect Industry Dynamics With Many Firms.” *Econometrica*, 76(6): 1375–1411, URL <https://doi.org/10.3982/ECTA6158>.
- Wiser, Ryan H., Dev Millstein, Ben Hoen, Mark Bolinger, Will Gorman, Joseph Rand, Galen L. Barbose, Anna Cheyette, Naïm R. Darghouth, Seongeun Jeong, Julie Mulvaney Kemp, Eric O’Shaughnessy, Bentham Paulos and Joachim Seel (2024). “Land-Based Wind Market Report: 2024 Edition.” Technical report, Lawrence Berkeley National Laboratory, URL <https://emp.lbl.gov/publications/land-based-wind-market-report-2024>.
- Wiser, Ryan H., Dev Millstein, Ben Hoen, Will Gorman, Joseph Rand, Joachim Seel, Galen L. Barbose, Anna Cheyette, Naïm R. Darghouth, Seongeun Jeong, Julie Mulvaney Kemp, Eric O’Shaughnessy and Bentham Paulos (2025). “Land-Based Wind Energy Technology Update: 2025 Edition.” Technical report,

Lawrence Berkeley National Laboratory, URL <https://emp.lbl.gov/publications/land-based-wind-energy-technology>.

Wollmann, Thomas G. (2018). “Trucks without Bailouts: Equilibrium Product Characteristics for Commercial Vehicles.” *American Economic Review*, 108(6): 1364–1406, URL <https://doi.org/10.1257/aer.20160863>.

A Data Details

Table 7 shows summary statistics for the production panel. Average prices increase over the 2018-2024 period; very high prices in 2021 are due to Winter Storm Uri, which hit ERCOT in February and caused widespread chaos throughout the grid, with several important transmission facilities failing, renewables unable to deliver electricity to consumers, and gas lines freezing. Prices were as high as \$10,000/MWh during the storm.

Generation and demand increased almost 25% over the period, with most of the additions coming in the 2022-2024 range. Curtailment increased over the period as well, as more renewables competed for a roughly fixed amount of transmission capacity. Regionally, the Far West had the most growth, with demand more than doubling between 2018 and 2024. Demand is otherwise concentrated in load centers like the Coast, North Central, and South Central. Generation is more evenly spread out, and renewable curtailment is most frequent in regions where generation outstrips demand.³⁴

The zonal load data is given for each of the eight ERCOT weather zones. I mapped counties in ERCOT to weather zones by hand. I combine this data with two products from the U.S. Energy Information Administration (EIA): data on electricity delivered to customers in 2020 (EIA Form 861 Part C, Delivery Companies) and utility service territories, which reports the counties served by each utility that delivered electricity in ERCOT in 2020 (Form 861, Service Territories).³⁵ The EIA data reports, for the calendar year of 2020, the total delivered electricity by sector (residential, commercial, industrial, and transportation) for each transmission and distribution utility that operated in ERCOT. I allocate those deliveries to counties based on a two-step weighting procedure. First, I look at a county's share of households (per the American Community Survey), and commercial and industrial employment (per the Census Bureau's County Business Patterns) within a utility's service area.³⁶ This yields the share of a utility's deliveries that are estimated to belong to each utility-county-sector pair. Then, I generate county weights based on each county's total utility deliveries across utilities. As a result, the EIA data determine the spatial allocation of load within weather zones, while the ERCOT data determine the level of load for each hour in the data.

³⁴Curtailment in the Eastern weather zone in 2020 is 12.7%, which comes from a single solar resource that entered the grid in November of 2020.

³⁵County load allocations are robust to using different years of EIA Form 861 data. Form 861 Part C begins in 2020. 6 of 214 counties have no coverage based on EIA data. All six of these counties are in the North weather zone, which has 44 counties; I assign all six 1/44 of North weather zone load and renormalize the other 38 county weights such that all weights add to one.

³⁶EIA also reports a small (<0.1%) share of electricity delivered for transportation purposes, which I allocate to counties based on their commercial employment share.

Table 7: Production Summary Statistics by ERCOT Weather Zone

Variable	2018	2019	2020	2021	2022	2023	2024
<i>Overall</i>							
Average price (\$/MWh)	37.9	46.2	24.2	169.5	72.6	62.7	29.8
Average generation (GW)	43.0	43.8	43.3	44.7	49.0	51.0	52.9
Average demand (GW)	43.0	43.8	43.4	44.8	49.2	51.0	52.9
Renewable curtailment (%)	2.3	2.4	4.3	5.1	4.9	4.2	4.7
<i>Coast</i>							
Average price (\$/MWh)	37.8	45.1	24.3	129.1	78.7	62.6	29.0
Average generation (GW)	9.4	9.9	9.5	10.2	10.2	10.7	11.3
Average demand (GW)	12.0	12.1	12.2	12.6	13.1	13.6	13.8
Renewable curtailment (%)	–	0.0	0.1	2.4	1.2	1.4	2.6
<i>East</i>							
Average price (\$/MWh)	37.3	45.0	24.3	202.2	77.3	65.6	29.3
Average generation (GW)	4.9	4.8	4.8	4.6	4.9	4.9	4.3
Average demand (GW)	1.7	1.6	1.6	1.7	1.8	1.8	1.8
Renewable curtailment (%)	–	–	12.7	1.3	0.5	1.0	2.5
<i>Far West</i>							
Average price (\$/MWh)	35.8	53.1	33.6	83.9	61.4	56.7	33.1
Average generation (GW)	2.7	3.1	3.6	3.5	4.2	4.5	4.8
Average demand (GW)	2.9	3.4	3.7	3.9	4.7	5.8	6.8
Renewable curtailment (%)	3.3	3.7	5.1	5.5	6.7	5.4	4.9
<i>North</i>							
Average price (\$/MWh)	35.5	40.6	18.1	172.0	66.7	59.4	23.5
Average generation (GW)	5.1	5.2	5.3	5.0	5.7	5.6	6.0
Average demand (GW)	1.0	1.0	0.9	1.1	1.3	1.4	1.7
Renewable curtailment (%)	2.5	2.1	4.3	5.7	2.7	3.2	4.4
<i>North Central</i>							
Average price (\$/MWh)	39.2	46.3	23.4	203.7	75.2	67.7	29.2
Average generation (GW)	9.6	9.6	8.8	9.1	10.6	11.7	12.2
Average demand (GW)	13.7	13.6	13.2	13.4	14.7	14.5	14.8
Renewable curtailment (%)	1.2	1.7	2.9	3.8	3.1	2.3	2.3
<i>South</i>							
Average price (\$/MWh)	36.9	43.7	21.4	155.5	54.0	41.7	26.6
Average generation (GW)	3.6	3.8	3.8	4.1	4.6	4.6	4.7
Average demand (GW)	3.5	3.6	3.5	3.6	3.9	4.0	4.2
Renewable curtailment (%)	1.0	1.5	4.1	6.2	6.7	5.9	7.2
<i>South Central</i>							
Average price (\$/MWh)	37.4	47.8	24.2	196.0	75.9	68.5	32.4
Average generation (GW)	5.4	4.9	4.6	4.7	5.3	5.3	5.7
Average demand (GW)	6.9	7.0	6.9	7.2	8.2	8.4	8.5
Renewable curtailment (%)	0.1	0.0	0.0	0.5	0.9	1.9	1.7
<i>West</i>							
Average price (\$/MWh)	34.7	40.4	20.0	176.1	66.5	62.4	31.3
Average generation (GW)	2.4	2.6	3.0	3.5	3.5	3.6	3.9
Average demand (GW)	1.4	1.4	1.4	1.4	1.5	1.4	1.3
Renewable curtailment (%)	2.6	2.5	4.1	3.8	5.5	4.7	6.0

Notes: Prices are hourly county LMPs weighted by estimated county demand. County LMP coverage begins July 1, 2018, so the 2018 price averages cover July–December; the remaining statistics cover the full calendar year. Generation is the SCED Base Point integrated over five-minute intervals. Overall generation includes all SCED resources. Renewable curtailment is $\max\{\text{HDL} - \text{Base Point}, 0\}$ for wind and solar divided by renewable generation plus curtailment. Regional rows are ERCOT weather zones.

226 substations appeared in the congestion data for congested elements on bulk transmission lines. Linking ERCOT’s congestion data to physical grid segments required a manual review of ERCOT substation names. I used ERCOT’s Major Transmission Element (MTE) datasets to map ERCOT’s abbreviated station names to full station names. There were several situations where substation names did not appear in the MTE data; in these cases, I performed review of other ERCOT and public reports to map the abbreviations to full substation names. I then matched full substation names to data from OpenStreetMap, a public infrastructure database that contains geolocations for electrical infrastructure worldwide. OpenStreetMap is frequently used in energy research (see, e.g., Medjroubi et al., 2017; Hörsch et al., 2018; Rivera et al., 2019). OpenStreetMap data provided precise locations for correctly mapped substations. For substations that did not have a corresponding entry in OpenStreetMap, I searched documentary evidence to determine the county that they were located in. I was able to successfully find county information for 215 of 226 total substations in the congestion data.

ERCOT also has a number of Generic Transmission Constraints (GTCs). GTCs monitor a collection of elements and control flows across all of them simultaneously. I identified 26 GTCs in the congestion data, all of which I was able to construct constituent transmission lines or geographic monitoring regions for.³⁷

³⁷Region-based GTCs monitor all of the flows into and out of regions. None of the region-based GTCs were used in the model of the grid described in Appendix B because they did not bind on bulk transmission lines sufficiently often.

B Prices and Quantities Under Arbitrary Grid Configurations

Entry to the electric grid is a function of expected prices and expected quantities. Prices and quantities, in turn, depend on the dispatch process: where electricity comes from and where it travels to. This section details the steps I take to estimate dispatch under any potential configuration of generation on the grid.

I describe this process in five steps. First, I give a brief overview of the network representation I use and my estimation of power flows.³⁸ Next, I describe the dispatch problem in more detail and how it maps to price formation at the nodal level. I then describe the two estimation tasks I have: estimating unobserved grid capacity and modeling the process by which the grid operator commits dispatchable units to produce. Finally, I discuss validation of the model I build.

B.1 Network

The representation of the grid that I use in this article treats counties as nodes connected by edges. Edges are based on the bulk transmission grid; when any two neighboring counties have at least one 230 kV or 345 kV transmission line connecting them, they are given an edge on the graph representation I use. In cases where multiple transmission lines connect two counties, I aggregate those transmission lines into a single edge.

ERCOT uses AC transmission. This means that grid operators cannot control where power travels on the network. Instead, grid operators turn generators on and allow demand to take power off the grid at places where its needed. This lack of control means that grid operators must be careful to not turn generators on in such a way that the flow of power will overload any transmission line on the grid. I now describe the process by which grid operators measure power flows on the network.

Power flows depend on net injections and a transmission line’s reactance (i.e., how strongly a line limits power flows) to power. Injections matter based on direction and size: nodes that inject electricity to the grid tend to push power towards nodes that withdraw electricity from the grid; larger injections push more power away from a node and larger withdrawals pull more power towards a node. Reactance depends on edge length and edge voltage. Longer edges have higher reactances, while higher voltage edges have lower reactances.

³⁸Note that my power flow estimation is intended to recover economically relevant congestion exposure and renewable revenues and makes assumptions that would be inappropriate for a full engineering model of the grid.

I assign each underlying transmission line in the grid a reactance rate of 0.32 ohms/km.³⁹ I calculate reactance for edge c_{ij} (which links nodes i and j) as a per km measure based on length L_c and voltage V_c :

$$X_c = \frac{0.32 \times L_c \times 100}{V_c^2} \quad (19)$$

Note that reactance rates are common across all edges. Assigning common reactances omits details about equipment like conductor material and transformers from my model. Further, because the grid connections I consider are almost entirely 345 kV lines, almost all heterogeneity in line reactance comes from line lengths (Kundur, 1994; Stott et al., 2009).

Power flows on edge c_{ij} can now be solved. I use a DC power-flow model to do solve for flows (DC power-flow models are common in industry, see Stott et al., 2009; Electric Reliability Council of Texas, 2022). I make several assumptions in order to estimate the DC power-flow model: I ignore resistance and line losses, which are less concerning at shorter distances (relative to, e.g., longer distance transmission considered by Hausman (2024)); and I assume net injections sum to zero (so the grid is balanced) and phase angle differences are small (so there are not blackouts and equipment still works). Allowing θ_i to represent a node's phase angle (which measures the net injection of node i relative to the rest of the network), power flows F_c on edge c_{ij} are equal to:

$$F_c = \frac{\theta_i - \theta_j}{X_c}. \quad (20)$$

Solving the grid operator's problem requires understanding how an injection at node i travels throughout the grid. To do so, I construct a nodal susceptance matrix, where edge susceptance is the inverse of edge reactance: $b_{ij} = \frac{1}{X_c}$. Let B be the nodal susceptance matrix, entries of which give the susceptance of all edges on the grid: $B_{ij} = -b_{ij}$. For unconnected nodes, entries are set to 0. Diagonal entries are the sum of susceptances for all edges connected to a node: $B_{ii} = \sum_{j:(i,j) \in \mathcal{E}} b_{ij}$, where $\mathcal{E}$ contains all edges connected to node i . Then, nodal balance is satisfied if $p = B\theta$, where p is the vector of county net injections and θ is the vector of all phase angles (Stott et al., 2009).

Phase angles are unidentified in levels; instead, they are defined in relation to a reference county (called a slack county in the literature). I set Harris county as the slack county and modify the B matrix by removing the Harris row and column, yielding the reduced matrix

³⁹Kundur (1994) reports positive-sequence series reactance of 0.367 ohms/km for a typical 345 kV overhead line and 0.325 ohms/km for a typical 500 kV overhead line. Some edges represent multiple transmission lines. I weight underlying edges in proportion to their length and calculate a weighted average reactance across all constituent lines for multiple line edges.

$\tilde{B}$.⁴⁰ The phase angle of each non-Harris county is then given by the following:

$$\tilde{\theta} = \tilde{B}^{-1}\tilde{p}. \quad (21)$$

$\tilde{B}^{-1}$ is the inverse of the reduced B matrix, $\tilde{p}$ is the vector of non-Harris net injections, and $\tilde{\theta}$ is the corresponding vector of phase angles.

Finally, we can calculate Power Transfer Distribution Factors $PTDF_{c,r}$, which describe how a one-MW injection in r changes power flows on edge c_{ij} (conditional on a one-MW withdrawal in Harris county). The PTDF for corridor $c_{i,j}$ from an injection in region r is given by the following:

$$PTDF_{c,r} = \frac{1}{X_c}[(\tilde{B}^{-1})_{i,r} - (\tilde{B}^{-1})_{j,r}] \quad (22)$$

Note that injections in region r can have effects on power flows far from the injection site. c does not have to touch r . PTDFs are bound by $[-1, 1]$, where negative numbers indicate power flowing in the opposite direction from a randomly chosen reference direction for a given corridor.⁴¹ Collecting all PTDFs in a matrix $PTDF$ shows how a one-MW injection in any region changes power flows throughout the grid.

The $PTDF$ matrix can be used to calculate flows on corridors across the grid. Given a vector of net injections p , the flows on edge c are given by:

$$F_c = \sum_r PTDF_{c,r} p_r. \quad (23)$$

Note that this construction of flows, which is what I use in estimation, does not rely on the assumption I made about reactance.

B.2 Grid Capacity

After reducing the network to the county-edge graph, I have 300 total edges for which I need capacity information. I estimate K_c in three parts. First, I set initial capacities for each edge in the graph. Initial capacities are based on direct limits taken from the shadow price data when available. The shadow price data only provides limits for transmission lines that are actively constrained. Of the 300 edges, 50 receive estimated limits based on the shadow price data. The remaining 250 edges receive capacities based on their voltage and

⁴⁰The reference-node choice is an accounting normalization: for any balanced vector of net injections, predicted physical flows are invariant to the choice of slack node.

⁴¹A PTDF is bound by $[-1, 1]$ because the injection is one MW.

the number of lines aggregated within a single edge.

Voltage measures the pressure that transmission exerts on power to flow in a given direction – not the maximum amount of electricity that flows along a given transmission line. The two are proportional however. I assume that all remaining 345 kV edges have a capacity of 1200 MW, which is the average binding limit for 345 kV transmission lines based on the congestion price data. For consistency, I assume that 230 kV transmission lines have a capacity of 800 MW.⁴²

In the second step of the process, I use evidence from observed dispatch. Based on observed net injections in a county – i.e., looking at, for each period from 2018-2024, observed generation and estimated demand – PTDFs allow me to calculate the implied flows on a given edge as follows:

$$F_{ct} = \sum_r PTDF_{cr}(q_{rt} - D_{rt}). \quad (24)$$

If an edge has direct evidence of an implied power flow greater than its initial capacity and it did not cause congestion during period t , I adjust the capacity of that line upwards to fit that data.

In the third step of the process, I solve the grid operator’s dispatch problem for each hour from 2018-2024. To do so, I reconstruct historical supply stacks using generator offers from the SCED data and observed dispatch limits.⁴³ Then I solve dispatch based on the current best guess of edge capacities.

I compare the solved dispatch model to observed outputs at the edge level. For each edge, I look at the spread between the model implied and observed nodal endpoint prices. I calculate 90th percentile spreads; if the model spread is too high, I increase edge capacity,

⁴²A 1,200 MW real-power limit on a balanced three-phase 345 kV AC circuit corresponds to a line current of about 2.0 kA:

$$I = \frac{1200 \text{ MW}}{\sqrt{3} \times 345 \text{ kV}} \approx 2.01 \text{ kA},$$

where I is line current. I interpret this value as a short-corridor thermal-capacity prior rather than a long-distance transfer capability. This distinction is consistent with engineering loadability guidance: AEP reports that 345 kV lines have much lower long-distance loadability under the surge-impedance-loading yardstick, but that short-distance loadability can be higher when conductor and station-equipment thermal ratings are adequate; it gives 1,500 MW on a 345 kV line as approximately 3.8 SIL over about 50 miles (American Electric Power, 2008; Dunlop et al., 1979). Consistent with NERC facility-rating standards, observed facility ratings depend on equipment ratings, ambient assumptions, operating limits, and verified engineering analysis (North American Electric Reliability Corporation). There are 25 edges with voltage classes of 230 kV. Assuming these edges have a capacity of 800 MW is consistent for a 230 kV line with a line current of about 2.0 kA. In reality, capacity depends on many factors, including conductor size, the number of conductors, weather, substation equipment, line length, and more.

⁴³I also account for committed units required output.

and if it's too low, then I decrease edge capacity.⁴⁴ Then I look at the modeled vs observed binding frequency for each edge. I define observed binding as anytime the edge's absolute endpoint price spread is greater than \$5/MWh.⁴⁵

This process results in small adjustments to modeled capacities. It increases flows for 3% of edges and decreases flows for 17% of edges. The maximum decrease is 356 MW, the 10th percentile decrease is 26 MW, and the 25th percentile decrease is 0 MW. Similarly, the maximum increase is 391 MW, while the 99th percentile increase is 61 MW and the 95th percentile increase is 0 MW. It improves the prices calculated by the dispatch model relative to the observed data by roughly 10%.

B.3 Commitment

This section describes the steps I take to account for unit commitment in the dispatch process. Unit commitment places a (sometimes large) stack of price insensitive dispatchable supply at the bottom of the offer stack. This shifts the offer curve for generators bidding into the market based on marginal cost to the right and depresses prices as a result. In order to have an accurate counterfactual model of prices and quantities, I must account for the grid operator's commitment behavior in equilibrium.

A model of endogenous commitment is outside the scope of this paper. Instead, I estimate a reduced form approximation of commitment each period. Estimating commitment requires two steps. First, I estimate the MW capacity of dispatchable resources available to commit each hour. I estimate availability separately for coal and natural gas. The model depends on unit online statuses. Online statuses reflect whether or not a generator is currently producing electricity. Online dispatchable resources must produce some electricity (or else they pay ramping costs to turn off). They are able to produce up to a High Sustained Limit (HSL) (Electric Reliability Council of Texas, 2022). I model the expected amount of available coal as equal to the sum of HSLs for all online coal units in a given hour.⁴⁶ I model the expected amount of available natural gas as the sum of HSL across online units, plus α times the HSL of all offline gas units. I find that setting $\alpha = 0.40$ produces the best fit with prices.

The second step of the commitment model estimates actual commitment. To estimate the model, I predict commitment separately by county and fuel based on local and system net

⁴⁴I look at 90th percentile spreads because differences are only informative when constraints are binding. Maximum spreads measure prices during blackouts, which are difficult to accurately price.

⁴⁵I use this criterion as an additional calibration diagnostic; the primary capacity adjustments target modeled-versus-observed 90th-percentile endpoint-price spreads.

⁴⁶This assumes that counterfactual entry would not change whether or not units were online in any given period.

load, renewable production, and system tightness, which measures how close system net load is to the total HSL of all online and offline coal and natural gas units. I include fixed effects for hour, month, and market-period.⁴⁷ The regression produces, for each counterfactual hour, dispatchable availability, which I apply to submitted coal and natural gas offer curves.

⁴⁷I include five market periods in the model: pre-Winter Storm Uri, from January 1, 2018 to February 12, 2021; Uri, from February 13 to 19, 2021; Post-Uri, from February 20 to June 7, 2021; 2021 Reform, from June 8 to December 31, 2021; and Post-reform, from January 1, 2022 onwards. ERCOT adopted a more conservative operating posture starting in summer of 2021, committing resources more actively. In 2022, ERCOT made changes to its Operating Research Demand Curve, which determines how the units that ERCOT forcibly commits get compensated for that commitment.