An Empirical Analysis of the US Generator Interconnection Policy*

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Abstract

Generators applying to connect to the US power grid go through an interconnection queue. Most wind and solar generators that begin the process do not complete it. We use new data to find that high interconnection costs are a key factor in generators' decision to withdraw from the queue. A longer queue also increases the average waiting time. We develop and estimate a dynamic model of the queue and quantify the effect of policy reforms on renewable generation capacity. Our counterfactuals quantify the effectiveness of subsidies for interconnection costs, a policy of smoothing costs across generators, and an approximate optimal queuing mechanism.

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1 Introduction

The transition to a low-carbon electricity grid will require massive investment in wind and solar-powered electricity generation. Yet, connecting an electricity generator to the US power grid is increasingly difficult. The process, known as interconnection, takes an average of nearly four years. It can also be costly: connecting generators are often required to upgrade the transmission infrastructure because the local grid is at capacity (Plumer 2023). Project developers cite interconnection as the single biggest hurdle they face (Driscoll 2022), and less than a quarter of the wind and solar generators that start the process complete it (Rand et al. 2021). We study the design of this interconnection process.

The interconnection process works as follows. A generator wishing to connect to the transmission grid joins a waitlist known as the "interconnection queue". The grid operator, also known as a regional transmission organization, conducts a series of engineering studies that determine whether the new generator will overload the grid ("violation"), what new equipment (such as new transmission lines) is needed to resolve the violation, and what the cost of this equipment and its installation will be ("interconnection cost"). Each subsequent study provides more certainty about the final cost. Generators in the queue must pay for the studies to remain in the queue, and they can drop out of the process at any time. After the final study, the generator can connect to the transmission grid by paying the interconnection cost, or it can leave the queue.

From an economic perspective, the current queuing process is far from optimal. Priority is entirely by entry date, but the probability of completion is significantly different across generators even when they are given the same final interconnection cost estimate. This results in many studies being done for generators with low probabilities of completion. The recent influx of interconnection requests further exacerbates congestion in the queue.

We study the market design of the interconnection process using a novel data set on the costs of interconnection. We hand collect these data for the PJM grid operator which has the most comprehensive public records of any US regional transmission organization. PJM serves 65 million people in parts of the Mid-Atlantic, Midwest, and Southern United States (PJM 2021*b*). We have collected data for generators that entered the queue from February 2008 through September 2020; they account for 4,085 out of the 6,461 total requests for interconnection in PJM.

Using this new dataset, we first document empirical evidence that high interconnection costs cause withdrawals. While the median interconnection cost estimate is low, the distribution of interconnection costs has a long right tail. In the second study, for example, the median interconnection cost is \$50,000/MW, the 75th percentile of this cost distribution is \$150,000/MW, and the 90th percentile is \$400,000/MW, roughly one third of the installation cost for wind and solar generators. Generators with a second study cost estimate above \$100,000/MW (the 66th percentile of the cost distribution) are 25 percentage points more likely to withdraw from the queue than generators with a cost estimate of zero. This is a 76 percent increase at the mean withdrawal rate of 33 percent. We also find that observably similar potential generators can have very different interconnection costs. This pattern is consistent with interconnection costs being difficult to predict ex ante. Finally, we find that renewable generators have higher interconnection costs than fossil fuel generators, even after controlling for distance to the existing grid infrastructure.

There is also a geographical cost externality which helps explain why some generators have such high interconnection costs. In many cases, new generators must pay the entire cost of the transmission upgrades they trigger even though existing and future generators also benefit. According to Gregory Wetstone, president of the American Council on Renewable Energy, "Today's grid interconnection policies are largely analogous to requiring the next car entering a crowded highway to pay the entire bill for a needed lane expansion" (Hale 2021*a*). We find that this externality is large but affects few projects, so its effect on overall completion rates is limited. Specifically, we show that a costly completed interconnection at the same interconnection point and within 10 km implies the next request is 61 percent more likely to have a zero interconnection cost estimate. Yet, this externality affects only about 10 percent of generators.

We next quantify the role of a congestion externality: when more generators are waiting in the queue, the rate at which studies are returned may slow. Starting in 2018 there was a dramatic rise in the number of generators queuing each year, and grid operators struggled to keep up with demand for interconnection studies. Perhaps the most striking example is PJM. It announced in 2022 that it would not start reviewing new interconnection requests again until 2026 while it works to clear its backlog (Howland 2022). We estimate a flexible probit model of the probability of new study arrival, controlling for a rich set of generator characteristics. PJM requires up to three engineering studies to estimate the interconnection cost. We find that the arrival probability of the first or second study does not significantly decrease when the queue size increases, but the arrival probability of the third study decreases sharply. Our estimates imply that a 10 percent increase in the length of the queue reduces the probability a generator receives the third interconnection study in a given quarter by 0.8 percentage points, or about 10 percent.

We then develop an empirical model of queuing to study the incentives of potential generators. We model withdrawal decisions as an optimal stopping problem, and we develop a tractable queuing equilibrium concept that accommodates the non-stationarity we see in the data. Using the model, we simulate the impact of three counterfactual policies. The first is a direct subsidy for interconnection costs for renewable generators. We first compare two forms of subsidy: (1) a percentage of the interconnection cost (e.g., 20% of the interconnection cost) and (2) a fixed amount per megawatt (e.g., $0.10 million/MW). To understand their effectiveness, we vary the levels of subsidy (changing the percentages or the amount of subsidy per megawatt) and quantify the equilibrium responses of the generators. On a per-dollar basis, we find that the percentage subsidy is more effective at increasing new capacity.

We also simulate a counterfactual that is a form of cost stabilization policy. A grid operator commits to charging a level of interconnection cost on a per-megawatt basis, with a subsidy program paying for the difference between the assessed costs and the actual interconnection costs. This exercise is similar to the reforms proposed by a number of transmission organizations that aim to reduce cost uncertainty. We find that this policy is less effective at increasing capacity than direct subsidies on a per dollar basis.

Finally, we consider an approximation of the optimal queuing policy, where generators are assigned different priorities based on observed characteristics. The intuition is that, by excluding generators with a low probability of completion, a queue planner reduces the queue size and delivers studies to other generators faster. More generation capacity will be completed if the marginal effect of faster study delivery is greater than the marginal effect of the exclusion. The approximate optimal policy prioritizes larger generators and reduces their waiting time, resulting in 8 percent more renewable capacity than the status quo.

Related Literature

This paper is the first empirical study on electricity market entry that carefully accounts for the effects of interconnection queues. Although the interconnection process has received some attention in research on energy policies (e.g., Gergen et al. (2008), Alagappan et al. (2011)), it has been rarely studied in the economics literature, likely due to a lack of data. In considering the economic implications of electricity transmission policy, this paper relates to papers studying the effects of transmission constraints on competition (Wolak (2015), Ryan (2021), Davis & Hausman (2016)), emissions (Fell et al. 2021), and investment in renewable energy (Gonzales et al. (2022); Doshi (2022)).

We also contribute to the literature on how public policy affects investment in renewable energy (see, e.g., Aldy et al. (Forthcoming), Hitaj (2013), Johnston (2019), Metcalf (2010)). We find that a better queuing policy may have comparable effects to multi-billion dollar subsidies. More broadly, there are a number of papers in the energy and environmental literature that study investment and industry dynamics (Ryan (2012), Gowrisankaran et al. (2016), Fowlie et al. (2016), Blundell et al. (2020), Butters et al. (2021), Elliott (2021), Gowrisankaran et al. (2022), Abito et al. (2022), Covert & Sweeney (2022), Davis et al. (2022)). The cited papers are unified in focusing on how environmental regulations interact with dynamic incentives in equilibrium.

Our study uses data from PJM, the largest transmission organization by the number of customers served. A number of papers (e.g., Mansur (2007, 2008), Bushnell et al. (2008), Allcott (2012)) also use data from PJM but focus on market structure issues, while Linn & McCormack (2019) study exit by coal-fired power plants in PJM.

Finally, we contribute to the market design literature by studying a queuing problem in a novel and important market. Several empirical studies (Gandhi (2020), Agarwal et al. (2021), Waldinger (2021), Verdier & Reeling (2021), Liu et al. (2021)) have considered market design in dynamic environments. We develop a tractable queuing equilibrium concept for a non-stationary environment, extending the equilibrium concept in Agarwal et al. (2021). Our equilibrium concept is similar to Weintraub et al. (2010), and we use a finite horizon assumption to capture the non-stationarity in the data (Igami (2017), Yang (2020)).

2 Background

2.1 PJM Interconnection Process

We first describe how PJM manages the interconnection process in more detail. The two main types of participants are developers and transmission owners. Developers (e.g., NextEra Energy) enter their potential projects (e.g. 2.5 MW Front Royal Solar Field in Virginia) in the queue and pay the interconnection costs identified in the studies. More specifically, a developer is a firm that owns and builds the facility that produces electricity. These developers can be either independent power producers (more common for renewable energy) or regulated utilities (more common for natural gas). A project is the power-producing facility that a developer will build at a specific location. We refer to a developer-project combination as a "generator" throughout the paper. Transmission owners are regulated utilities and oversee the interconnection studies. Studies are usually done by the owner of the local transmission network, but they may also be done by contractors under the direction of the transmission owner (Connell & McGill 2020). Transmission owners also construct the network upgrades identified in the studies.

A number of reforms over the years changed the guidelines on review time for each study, but the basic structure has not changed. Potential generators can apply to be in the queue over a 6-month window, twice every year. Projects that apply in the same 6-month window are put in the same cohort and will receive up to three studies (feasibility, system impact, and facility study) sequentially. Through these studies, generators learn increasingly accurate information about the costs of interconnection. To receive the next study, a generator must incur a cost, but the generator can freely leave the queue at any time. PJM may require just one or two studies for some smaller projects (often less than 20 MW). After the last study is issued, the generator chooses to leave the queue or pay the final costs to interconnect, thus completing the interconnection process. Construction is usually completed within two years, and the generator goes online.

To enter the interconnection process, developers must secure land sufficient to build the project,[1] a requirement that discourages speculative projects. This requirement is known as site control, and was instituted by PJM around 2010 (Pincus 2010, Porter et al. 2009). If a developer has multiple generators in the queue, the land secured must be sufficient to build all generators (PJM 2021*f*). Developers must also pay a deposit to enter the queue or move on to the next stage. Ninety percent of this deposit is refundable. The deposit amount depends on project size and the stage, with larger projects and later studies typically requiring higher deposits. For the median project size of 20 MW, the three deposits would be 12,000, 10,000 and 50,000 dollars per megawatt. Generators that withdraw have their deposit returned, less the non-refundable portion and any study costs already incurred. (PJM 2021*c*).

The official timeline for the interconnection process is quite rigid. For projects that apply within the same time window, PJM starts conducting the first studies (feasibility studies) one month after

[1] A common approach is to lease the land or have an exclusive option to lease, but a developer could also purchase the land.

the closing of the window. Within three months, generators are supposed to receive their first studies. At this point, generators have another month to decide whether to advance to the second study (system impact study). The second study then takes four months, at which point generators have one month to decide whether to request the third and last study (facility study). The third study takes 6 months. Finally, generators and PJM agree on final details and sign the construction agreement over a 6.5-month period (PJM 2021*a*). A project may suspend the process for up to 3 years (up to 1 year if the suspension has a negative impact on subsequent projects), though these suspensions are uncommon (PJM 2021*e*).

Despite this timeline, significant delays in delivering studies can occur due to the number of backlogged projects and a lack of staff capacity (Shoemaker 2021). A generator has approximately one month to decide whether to pay the deposit and receive the next study, but it has little control over when the transmission organization delivers the study. A solar developer in PJM recently lodged a complaint with Federal Energy Regulatory Commission (FERC) after waiting more than two years for the second study (Hale 2021*b*).

We assume that the transmission organization does not exercise market power and charge an interconnection cost higher than the cost of upgrades in a competitive factor market. Although connecting generators pay for this construction, the transmission owner owns the resulting infrastructure.[2] Yet, the transmission owner does not profit from owning these upgrades because they do not go into its rate base.

2.2 Timing of Interconnection within Project Development

Generators apply for interconnection early in the project development process. Wind and solar generators follow similar timelines, and Appendix Figure A.1 reproduces a typical wind project development timeline from AWEA (2019). A generator first secures the land necessary to build the project, then enters the queue. The permitting and interconnection process usually occur simultaneously.[3] Renewable energy generators then sign long term contracts to sell the power near the end of the interconnection process or once it is completed. Financing in renewable energy is done at the project level rather than the developer level, and a long term contract to sell the power is usually necessary for financing (Johnston 2019). After the long term contract and interconnection service agreements are signed, the physical generator is constructed. This construction typically takes a matter of months, far shorter than the time the generator spends in the queue.

The interconnection process may interact with other necessary steps in project development. Power buyers such as utilities award many long term contracts to renewable energy generators via a system similar to a procurement auction. A potential buyer of renewable power will issue a request for proposals and then choose the most desirable to sign a long term contract with. A wind developer we spoke to said a good interconnection queue position increases the chance a project

[2]It is possible but uncommon for projects in the queue to be owned by the transmission owner.

[3]Trouble acquiring the necessary permits is another reason energy projects fail, but developers perceive interconnection delays and costs as the more important hurdle (RechargeNews (2021), Collier (2021)).

will be chosen. Permitting may interact with the interconnection process because a project may need permits to build the network upgrades identified in the interconnection process.

These interactions make waiting costly. Beyond the cost of delaying expected profits, a long and uncertain delay can make it harder for developers to secure a long term contract to sell the power. A long wait may also cause a developer's option to lease to expire. In this case, the developer will need to relinquish the site control or renegotiate with landowners.

2.3 Speculative interconnection requests

A natural response to unpredictable interconnection costs would be for project developers to enter several interconnection requests with the intention of building one project. Because study fees are low and deposits are refundable, the main cost of this strategy is the cost to secure the land for all queue entries. To check whether this behavior is an import feature of generator behavior, we use data on the developers associated with each interconnection request. We observe this information for about half of the generators. We do not observe it for projects that dropped out early in the process.

It does not appear that developers frequently spam the queue with many requests per viable project. Within a cohort (defined by a 6-month queue entry period), 79 percent of projects are the only project by that developer. Of the cases where a developer had multiple queue requests in a cohort, 64 percent either completed or withdrew all their projects. This evidence is consistent with the following quote.

> *Maybe there are some people who carpet bomb the queues with speculative projects, but I think in general they appear to be speculative because people know it's going to take five years to get through the process, so you have to do that early on. It would be unwise to fully develop your site prior to entering a queue that you have no certainty on getting through, especially because so many things can change in five years.*- Boone Staples, director of transmission analysis at Tenaska (Penrod 2022)

Although we expect longer wait times to cause developers to enter the queue earlier in project development, we do not endogenize entry in the dynamic model. Instead, we will test robustness to different assumptions about how counterfactual policies might affect entry into the queue.

2.4 Larger Scale Transmission Investment

While new generators pay for transmission network upgrades through the interconnection process, other transmission investment is planned by the grid-operator. In PJM, this transmission planning process is called RTEP, which stands for regional transmission expansion plan. The primary goal of the RTEP is to maintain reliability (PJM 2021*d*).

At a high-level, the two types of transmission investment are substitutes, but they are funded differently. Connecting generators pay for the network upgrades they trigger through the interconnection process. In contrast, electricity consumers pay for RTEP investment via higher transmission rates. The allocation of RTEP costs to transmission rates varies by project type. RTEP investment can either be baseline projects planned by PJM or supplemental projects planned by the transmission operators. Baseline project costs are allocated across PJM load zones based on the zone's usage of the upgrade, while supplemental project costs are allocated to the zone the project is located in (PJM 2021*d*, Lieberman 2021).

In our analysis, we treat RTEP investment as fixed. Twenty-seven billion dollars worth of RTEP investment was placed in service from 2008-2020 (PJM 2023). We find that locations with RTEP are more likely to see entry by generators. Locations with recent RTEP investment are also associated with a moderate decrease in interconnection costs (Table A.1). While generator entry may respond to RTEP, the RTEP process does not try to anticipate entry by generators: PJM's planning of baseline projects is based only on generators that have already completed the interconnection process (PJM 2021*d*).

2.5 Proposed Reforms

There have been several recent efforts to reform the interconnection process, which a key regulator described as in "chaos" (Potter 2021). The Federal Energy Regulatory Commission (FERC) oversees US transmission policy, and it issues rules that apply to all interstate transmission organizations. Transmission organizations, like PJM, then decide how to organize their queues within FERC's framework. Both FERC and the individual transmission organizations have started to implement reforms.

In 2022, FERC proposed new rules governing the interconnection process. These rules will be part of FERC's first major transmission rulemaking since 2011 (Morehouse 2021).[4] Broadly, the rules try to transition interconnection queue priority from "first-come, first-served" to "first-ready, first-served". The rules increase "financial commitments and readiness requirements" for generators to receive interconnection studies, move from separate studies for each generator to studying several proposed generators together, and penalize transmission providers for delays in completing studies (O'Driscoll 2022).

PJM plans to implement reforms consistent with FERC's proposed new rules, and FERC approved these reforms in November 2022 (FERC 2022). PJM will group projects into clusters and study all projects in a cluster jointly. By having all projects in a cluster move collectively through the queue and make decisions at the same time, PJM envisions that developers will have more cost certainty as they progress from one phase to the next. PJM will also require deposits equal to a larger share of the generator's estimated network upgrade costs, with the share increasing with each of the three study phases. There will also be stricter site control requirements: projects must demonstrate site control throughout the process rather than only upon entering the queue. With the tightened requirements, PJM aims to limit the number of projects less likely to complete the interconnection. Finally, for projects that PJM determines will have minimal network upgrade costs, there will be an expedited process (PJM 2022).

[4] A rulemaking is an instance where a federal agency can rewrite rules.

3 Descriptive Statistics and Regressions

This section presents the main empirical patterns that motivate the model. Our main data are based on the 4,085 interconnection requests in PJM from 2008 to 2020. These data come from pdfs of engineering studies done as part of the interconnection process. Because the formats are irregular, we hand collect these data. We start our sample in 2008 because data before 2008 have even more irregular formats, making it hard to identify the relevant interconnection costs. We also use data from PJM on the queue date and withdrawal or completion date for all generators that applied for interconnection from 1997 to 2020. The latter data allow us to construct accurate measures of the size of the queue. Summary statistics for the 4,085 requests (7,058 studies) in our sample are presented in Table 1.

Table 1: Summary Statistics

	Study 1		Study 2		Study 3	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Cost/MW	0.13	0.46	0.17	0.48	0.10	0.17
Log of (Cost/MW+1)	0.09	0.20	0.12	0.22	0.09	0.12
Base Cost/MW: <=0.01m	0.41	0.49	0.30	0.46	0.20	0.40
Low Cost/MW: (0.01m, 0.05m]	0.20	0.40	0.20	0.40	0.31	0.46
Mid Cost/MW: (0.05m, 0.1m]	0.14	0.35	0.17	0.37	0.20	0.40
High Cost/MW: >0.1m	0.25	0.44	0.33	0.47	0.28	0.45
Wait time (mos.)	5.35	2.69	12.61	11.18	18.37	12.77
Build new substation	0.15	0.35	0.20	0.40	0.45	0.50
Distance to substation (km)	3.82	6.01	3.71	6.18	3.39	5.23
Log distance to substation	0.45	1.53	0.34	1.59	0.36	1.51
Ordinance	0.29	0.46	0.32	0.47	0.33	0.47
Size (MW)	97	195	105	191	172	291
Coal, Oil, Diesel	0.02	0.13	0.01	0.12	0.01	0.09
Natural Gas	0.17	0.37	0.16	0.36	0.26	0.44
Wind	0.09	0.29	0.10	0.30	0.13	0.33
Solar	0.60	0.49	0.60	0.49	0.55	0.50
Battery	0.10	0.30	0.10	0.30	0.03	0.17
Other	0.03	0.18	0.03	0.17	0.03	0.16
N	4,054		2,432		572	

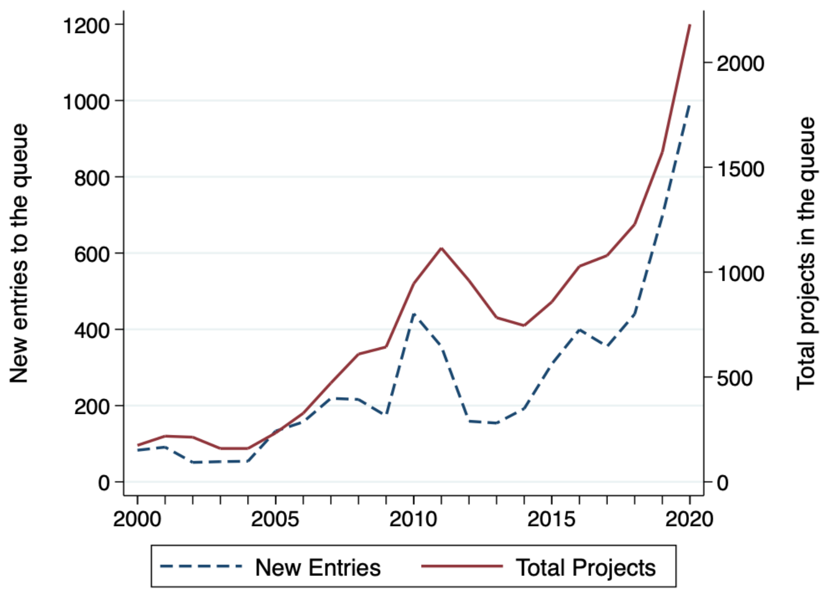
Generators entering the queue in 2008-2020. Costs in millions of 2020 dollars. Cost/MW is interconnection cost estimate divided by the generator's size in MW. Wait time for Study 1 is wait in months for the first study after joining the queue. Wait time for Study 2 wait in months for second study after receiving the first study. Wait time for Study 3 wait in months for third study after receiving the second study. Build new substation is an indicator for whether the study indicates a new substation is necessary. Distance to substation is the distance to the nearest substation in kilometers. Ordinance is an indicator for a local ordinance restricting renewable energy development.

3.1 Interconnection Requests

The PJM queue is dominated by requests for natural gas, wind, and solar generators. These three fuels accounted for 82 percent of interconnection requests from 2008-2020. Natural gas generators tend to be much larger than wind and solar generators; they account for 14 percent of requests but 40 percent of requested capacity. Appendix Figure A.2 shows the proportion of new requests by fuel type in each of our sample years.

The number of interconnection requests has increased over time. Figure 1 shows both the number of new interconnection requests each year (dotted line) and the average number of projects in the queue by year (solid line). Requests increased dramatically starting in 2015. This increase was driven by renewable generators. Because renewables are smaller on average, the increase in requested capacity was less pronounced: the capacity of new requests in 2008 was 42 GW compared to 69 GW in 2020. The spike in 2010 was due to an influx of solar generators. The likely cause was a temporary program that offered the federal subsidy for solar investment as a cash grant rather than a nonrefundable tax credit (Aldy et al. Forthcoming).

Figure 1: Queue size over time



3.2 Interconnection Costs

We use cost per MW as our measure of cost and control for project size in all regressions.[5] We focus on costs from the second study because the first study does not typically indicate a generator's

[5]There do not appear to be economies of scale for moderately sized projects. For projects from the 10th to 90th percentile in size, a 1 standard deviation increase in capacity is associated with 0.05 standard deviation decrease in the Study 2 cost per MW estimate. Yet, the very smallest (largest) projects have significantly higher (lower) mean costs per MW.

contribution to shared network upgrade costs. We note that this is a selected sample because projects with high interconnection costs are more likely to drop out after the first study.

While the median interconnection cost estimate is close to zero, this cost distribution has a long right tail. Table 2 shows the distribution of Study 2 interconnection costs per MW. Thirty percent of projects have interconnection costs less than 0.01 million per megawatt. Yet, the 90th percentile of the cost distribution is 0.40 million per megawatt. For comparison, installation costs for wind and solar generators are roughly 1.5 million per megawatt.

Table 2: Distribution of interconnection costs

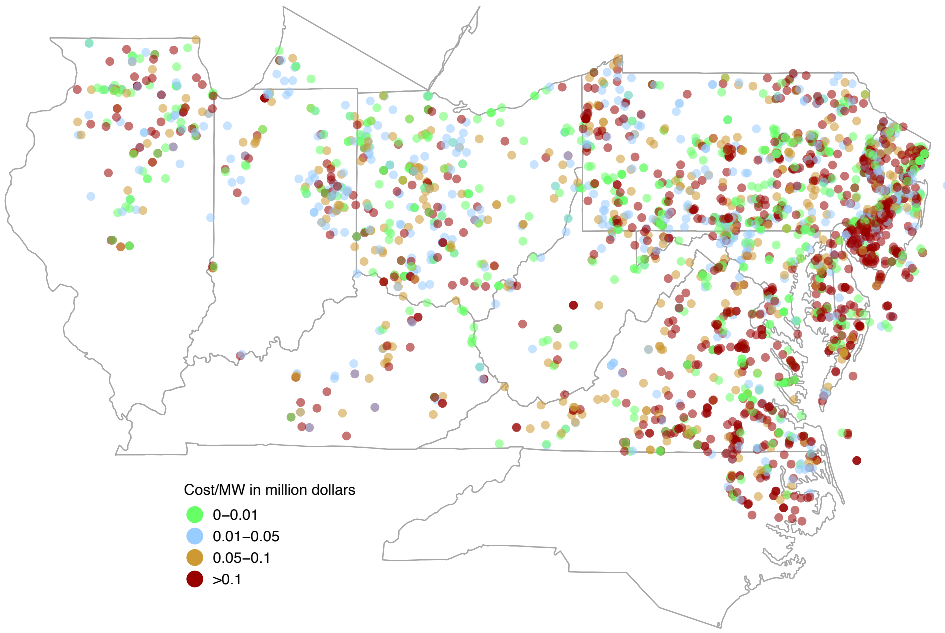
	Mean	SD	p50	p75	p90	p95
All	0.17	0.48	0.05	0.14	0.40	0.72
2008-2012	0.15	0.34	0.05	0.14	0.38	0.73
2013-2016	0.10	0.25	0.03	0.11	0.24	0.40
2017-2020	0.21	0.58	0.06	0.16	0.51	0.81
Renewable	0.20	0.51	0.07	0.17	0.45	0.78
Other	0.07	0.3	0	0.04	0.15	0.37

Distribution of Study 2 interconnection cost estimates in millions of 2020 dollars/MW.

Interconnection costs have also increased the last few years. The mean Study 2 interconnection cost estimate for projects queuing in 2017-2020 was roughly double that for projects queuing from 2013-2017. A similar pattern holds for other moments of cost distribution. This pattern is consistent with recent articles claiming interconnection costs are increasing as the U.S. grid becomes more congested (see, e.g., Caspary et al. 2021). Perhaps more surprisingly, interconnection costs have not always increased with time; they were higher for projects queuing in 2008-2012 than in 2013-2016.

Heterogeneity in interconnection costs is not primarily explained by geography. Figure 2 plots the location of projects with Study 2 cost estimates. More projects are clustered along the more populated east coast, and these projects have higher interconnection cost estimates, on average. But interconnection costs can vary substantially in the same geographic area, even within fuel type. Appendix table A.1 shows that characteristics such as size, state, fuel type, and year of entry explain only a quarter of the variation in interconnection costs. Renewable energy generators (wind and solar) have higher interconnection cost estimates per megawatt on average. The mean Study 2 cost estimate for renewable generators is is 0.21 million per megawatt, compared to 0.07 million per megawatt for fossil fuel generators. These costs are expressed as cost per capacity. Because the necessary transmission upgrades are determined based on maximum generation capacity, this difference in costs is not explained by renewable generation being intermittent. A more likely explanation is that renewables tend to be built in rural areas where the transmission network is less developed.

Figure 2: Costs by location



3.2.1 Interconnection Costs Drive Withdrawals

We next test whether high interconnection costs cause projects to withdraw from the queue. We look at the relationship between study cost estimates and whether a project withdraws from the queue or continues in the queue until the next study arrives. While Study 2 costs are a better measure because they include a project's contribution to network upgrades, we also present results for Study 1 costs. Because interconnection cost estimates are sometimes zero, our preferred specifications bin interconnection costs into four groups. The omitted group has interconnection cost estimates less than 0.01 million per megawatt.

We find a strong relationship between interconnection costs and a generator's decision to withdraw from the queue. When our cost measure is the log of interconnection costs plus 1 (Table 3 columns (1) and (4)), we find a statistically significant positive effect of interconnection costs on withdrawals for both Study 1 and Study 2. Results for the binned specification are presented in columns (2) and (5). While the coefficients on the Study 1 bins are not precisely estimated, the point estimate for the high cost bin implies that a high interconnection cost leads to a 7 percentage point increase in the probability a project withdraws relative to a project with a cost less than 0.01 million per megawatt. This is a 23 percent increase at the mean withdrawal rate of 31 percent. For Study 2, the estimated effect is larger and more precisely estimated. A high interconnection cost increases the probability of withdrawal by 25 percentage points, a 76 percent increase.

While it seems likely this relationship is due to interconnection costs causing withdrawals, we next consider alternative explanations for these results. One concern is that these estimates are

Table 3: Interconnection Costs on Probability of Withdrawing from the Queue

	Study 1			Study 2		
	(1)	(2)	(3)	(4)	(5)	(6)
Log of (Cost/MW+1)	0.335***			0.549***		
	(0.097)			(0.205)		
Low Cost/MW: (0.01m, 0.05m]		-0.027	-0.027		0.119	0.125
		(0.058)	(0.059)		(0.074)	(0.078)
Mid Cost/MW: (0.05m, 0.1m]		0.043	0.039		0.076	0.081
		(0.068)	(0.070)		(0.087)	(0.089)
High Cost/MW: >0.1m		0.088*	0.073		0.251***	0.260***
		(0.053)	(0.055)		(0.077)	(0.088)
Build New Substation	0.043		0.045	0.008		-0.039
	(0.057)		(0.061)	(0.078)		(0.082)
Log Distance To Substation	-0.004		-0.001	-0.000		-0.002
	(0.016)		(0.017)	(0.019)		(0.020)
Ordinance	-0.123		-0.112	0.067		0.047
	(0.083)		(0.082)	(0.143)		(0.154)
Observations	971	971	971	434	434	434

Projects queuing from 2011-2017; projects still active in Oct 2022 excluded. SEs in parentheses; clustered by substation. Dep. var. are indicators for projects withdrawing from the queue after receiving Study 1 and withdrawing after receiving study 2 (means: 0.31 for Study 1, 0.33 for Study2). Cost/MW is the interconnection cost estimate in the study divided by the project's size in MW. Build new substation is indicator for whether the study indicates a new substation is necessary, distance to substation is the distance to the nearest substation, and ordinance is an indicator for a local ordinance restricting renewable energy development. All specifications control for the size, fueltype, state, and nearest substation of the project studied, the year the project enter the queue, and the year the study is issued.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

instead capturing the effect of permitting difficulties on withdrawals. Projects in the queue are often simultaneously applying for permits. While we generally expect the permitting process to be independent of the interconnection process, projects may need permits to build the transmission infrastructure upgrades identified in the interconnection process. An inability to get these permits might cause projects to drop out of the queue even if they are willing to pay the high costs to build this infrastructure. For permitting costs, we test robustness to the inclusion of three permitting control variables. The first is whether the study indicates the project must build a new substation. Because this is entirely new construction, we expect it to require permits. The second is the distance between the project and the requested interconnection point. The idea is that the farther away the generator is, the more difficult it will be to acquire permits to site the necessary attachment lines. Finally, we control for whether the county the project is located in had an ordinance restricting the siting of wind and solar energy. This variable may proxy for overall regulatory stringency. Table 3 columns (3) and (6) show that our estimates are not affected by the inclusion of these controls.

Another concern is selection, especially for the Study 2 results. Generators that make it to Study 2 have already received a signal about their interconnection costs in Study 1. Generators with high Study 1 cost estimates that continue on to Study 2 may do so because they have unobservably high expected profitability. This selection would attenuate the relationship between interconnection costs and withdrawals. So, while it would bias our estimates, this selection would not affect our overall conclusion that costs interconnection costs drive withdrawals. Results are also quantitatively similar, though less precisely estimated, if we control for Study 1 costs in the Study 2 regressions.

3.2.2 A Geographical Cost Externality

Interconnecting generators complain the transmission network upgrades they pay for benefit other generators. We next test whether a costly interconnection benefits the next interconnecting generator in the same location. PJM shares network upgrade costs across contemporaneous generators (typically, those within the same or adjacent cohorts) that trigger the same violation. We define "next" as the next generator that does not share costs with the completed generator. Our threshold for costly is a *total* interconnection cost above 0.1 million.[6] Given these defintions, about 10 percent of projects in our sample are the next generator after a costly interconnction.[7]

We regress whether a generator has a low interconnection cost estimate on whether the most recently completed interconnection in the area was costly. Specifically, our dependent variable is an indicator for an interconnection cost estimate less than 0.01 million per MW. Many Study 2 interconnection cost estimates are zero, and we choose this low threshold rather than zero because small generators are disproportionately likely to have an estimate of exactly 0. A power engineer we spoke with suggested these externalities would be highly local, so we test for this effect for generators i.) connecting at the same substation and ii.) less than 10 km from each other. The independent variable of interest is an indicator for if the last completed interconnection request meeting these two requirements, if any, had a significant final interconnection cost. We control for the size, fuel type, state, and nearest substation of the generator studied as well as the year the study is issued, and we estimate this model for both Study 1 and Study 2 costs. Appendix Table A.2 reports summary statistics for the sample used in these regressions.

Table 4 shows that a costly interconnection leads to a large increase in the probability the next generator receives a low interconnection cost estimate. The left three columns show the effect on the Study 1 cost estimate, while the right three show the effect on the Study 2 estimate. Column 1 show that a costly prior interconnection increases the probability of a low Study 1 interconnection cost estimate by 12 percentage points. At the mean probability of 0.43, this is an increase of

[6] We use a total cost threshold because we expect interconnections with a high absolute cost to be more likely to have positive spillovers to the next project, but results are qualitatively similar if we instead use a cost per MW threshold to define costly.

[7] Because relatively few projects are affected, we will find that this externality is not very important in the counterfactual simulations. A caveat is that few projects are affected conditional on PJM's policy of cost-sharing for contemporaneous generators. If there were less cost-sharing, then more projects might be affected.

Table 4: Prior Costly Interconnections and Probability of a Low Interconnection Cost

Costly Prior Interconnection ...	Study 1			Study 2		
	(1)	(2)	(3)	(4)	(5)	(6)
Prior cost >0.1m	0.122***		0.119***	0.209***		0.210***
	(0.040)		(0.040)	(0.054)		(0.054)
Prior cost (0.1m, 0.5m]		0.182***			0.179**	
		(0.064)			(0.087)	
Prior cost (0.5m, 3m]		0.111*			-0.001	
		(0.065)			(0.080)	
Prior cost >3m		0.076			0.383***	
		(0.062)			(0.071)	
Two interconnections ago			0.043			-0.021
			(0.071)			(0.058)
Observations	2,828	2,828	2,828	1,572	1,572	1,572

Projects queuing from 2011-2020 (prior completions from 2008-2020). SEs in parentheses; clustered by substation. Dep. var. is an indicator for an interconnection cost estimate less than 0.01 m/MW (means: 0.43 for Study 1, 0.34 for Study 2). Costly prior interconnection refers to the prior completed interconnection at the same substation & within 10km. Baseline cutoff for costly is total interconnection cost greater than 0.1m. Two interconnections ago is whether the second to last interconnection at the same substation and within 10km was costly. All specifications control for the size, fuel type, state, and nearest substation of the project studied as well as the year the study is issued.

28 percent. For Study 2 (Column 4), the effect is even larger at 21 percentage points, a 62 percent increase. Columns 2 and 5 allow the effect to vary by the total interconnection cost of the prior interconnection. For Study 2, there is some evidence that the effect is largest for prior interconnections with the highest cost. Though we can reject the hypothesis that the coefficients on all three bins are the same, the non-monotonicity is difficult to explain. We also do not see the same pattern for Study 1. Finally, columns 3 and 6 add an indicator for if the second to last completed interconnection in the same location was costly. We do not find effects of this interconnection, suggesting the benefits from interconnecting after a costly completed interconnection are short-lived.

3.3 Waiting times

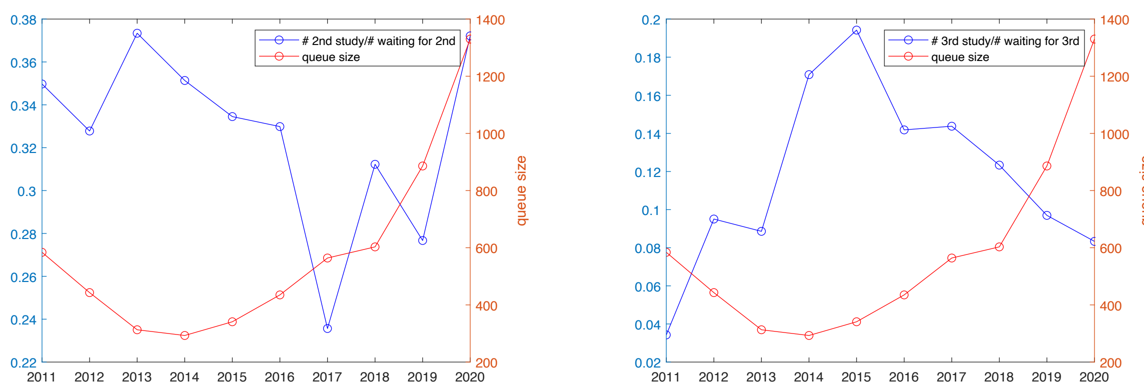
Generators spend a significant amount of time waiting for interconnection. The mean waiting time to receive the terminal study is 15 months. The first study arrives quickly, with over three quarters of projects receiving it within 6 months. The second study's arrival time is more variable. The mean wait time for the final version of the second study is 12.5 months with a standard deviation of 12 months. One reason for the variability in study 2 arrival is that it sometimes needs to be revised.[8] There is also more viability in the type and depth of analysis necessary in later studies. Time spent in the queue has also increased, though not as dramatically as the number of projects. The mean wait time to receiving the second study was 11 months for projects queuing in 2008-2012 compared to 15 months for those queuing in 2013-2017.

A Waiting Time Externality

We next study how the size of the queue affects the rate at which projects receive their studies. A congestion externality would imply that, when more projects are in the queue, studies are returned more slowly. To provide some motivation, we plot the proportion of projects eligible for a 2nd study that actually receive one in each year. We do the same for projects eligible for the third study. As PJM has reformed its queuing policy over time to avoid adding to the backlog, we use the more recent projects (queued after 2008) to compute the number of projects in the queue. Figure 3 shows that the arrival probability of the second study reverts to the 2011 level despite the large queue, after experiencing a decline in 2017. However, the third study arrival probability is highly negatively correlated with the queue size. In Section 5.1, we formally estimate the arrival process after controlling for a large number of project characteristics and still find that the queue congestion mainly affects the arrival of the third study.

Figure 3: Queue Size and Study Arrival

Second Study　　　　　　　　Third Study



4 A Model of the Interconnection Queue

To quantify the effects of possible policy reforms, we develop a finite horizon, discrete-time non-stationary dynamic model of the interconnection queue. In this model, each generator waits for a

[8] Twenty-five percent of projects in our sample had their second study revised. Revisions can be due to the connecting generator changing its request or nearby generators dropping out of the queue. We will model the arrival of the final version of each study, not the intervening versions which are not always posted by PJM.

maximum of $T = 20$ quarters, and generators arrive exogenously over time from 2008 to 2020. We start by describing the timing of the queue in each period.

At a high level, a generator faces an optimal stopping problem. The decision problem starts when the generator is issued the first study. The first study may be the final study, in which case the generator decides whether to complete the interconnection or withdraw. If the first study is not the final study and PJM requires a second study, the generator may choose to pay a fee and request the second study. The issuance of the study is stochastic, and in every period the generator decides whether to wait for the new study or withdraw. The second study again may or may not be the final study, and a similar decision problem repeats. Should PJM require the third study, the study will be the final study. Below we describe the timeline:

1. At the beginning of a period t, a generator observes the cost estimate from the latest study and other time-varying characteristics, such as the current calendar time, how many studies the generator has received, and whether certain engineering tests have been conducted;

2. The generator forms beliefs about whether the next study will arrive in the current period, the new cost estimate and other contents of the study. It decides whether to withdraw or continue to wait.

3. For the generators that choose to wait, they are issued new studies with some probability. For generators with one study,

   (a) With some probability the new study is the final study. The generator observes the final cost estimate and decides whether to complete the interconnection process or withdraw;

   (b) With some probability the new study is not the final study. The generator observes the cost estimate and other contents of the study and decides whether to request the next study or withdraw.

   For generators with two studies, the next study is the final study. With some probability the study is issued and the generator decides whether to complete the interconnection process or withdraw.

   If no new study is issued, the generator continues to the next period.

4. New generators enter the queue.

We next specify the decision problem of a generator.

4.1 Generator Decisions in the Queue

4.1.1 Notation

We focus on a particular generator's decision and omit the generator subscript in our notation. A generator in period t is associated with the time-invariant generator characteristics x such as the size of the generator. While in the queue, the generator incurs a waiting cost of $o(\tau, \tilde{\tau}, t, x)$, where τ is the number of periods a generator has been in the queue, and $\tilde{\tau}$ is the number of periods since receiving the last study. By linking the waiting cost to when the last study is received, the waiting cost accounts for study fees and deposits PJM charges for a generator to advance in the queue. We use c to denote the cost estimate from the latest study, and we use z to denote other information from previous studies.[9] We assume that every generator enters the queue with a first study, and we use $k \in \{2, 3\}$ to indicate which study the generator is waiting for. We use S to represent the potentially high dimensional vector of variables describing the queue status that may affect the study arrival probability and the interconnection cost. In theory, the variable S is the collection of the current calendar time t and the states of every past and current generator at t. We define S explicitly in Section 4.1.4. We use $\pi(S_t, x)$ to denote the expected discounted operating profit from the generator's future production when it completes the interconnection process in period t. Explicitly including S_t allows us to account for how the equilibrium queue outcomes may affect the expected payoff. For example, existing entrants may decrease the expected profitability of the focal generator. We assume that the support of $(c, z, \tau, \tilde{\tau}, k, t, S_t, x)$ is discrete.

4.1.2 Belief Assumptions

Suppose the cost estimate from the previous study is c. We assume the arrival probability of a third study with a cost estimate is c' in period t is

$$r(c'; c, z, \tau, \tilde{\tau}, t, x) \equiv H(c'; c, z, \tau, \tilde{\tau}, S_t, x), \tag{1}$$

where the function H is the probability of PJM issuing the new study given the current status of the queue and the generator state. Thus, we require beliefs to be consistent with the equilibrium queue status S_t but abstract from more complex beliefs based directly on the status of the queue. The arrival probability of a second study that is the final study with a new cost estimate c' is

$$p(c'; c, z, \tau, \tilde{\tau}, t, x) \equiv H_0(c'; c, z, \tau, \tilde{\tau}, S_t, x), \tag{2}$$

This is the probability that a second study arrives, and PJM deems a third study to be unnecessary.

Finally, we assume that the arrival probability of a second study that is not the final study (i.e. a third study is required) with a cost estimate c' and new information z' in the study is

$$q(c', z'; c, z, \tau, \tilde{\tau}, t, x) \equiv H_1(c', z'; c, z, \tau, \tilde{\tau}, S_t, x). \tag{3}$$

In our setting, at most three studies are issued. In both r and p, we assume that generators only form beliefs about the costs which will directly enter the payoff function as the generator decides whether to accept this final cost estimate and complete the interconnection. In q, the generator

[9] The information may be cumulative. For example, each study contains different engineering tests, and a generator needs to aggregate these results to form beliefs about the final interconnection cost.

forms the beliefs about the costs and other contents of the study z.

4.1.3 Generator Decision

We start from the last period a generator is in the queue, $\tau = T$. We assume that the generator faces an outside option (scrapping the project and relinquishing site control) valued at $b(t,x) + \xi_t$ in period t. If $\tau = T$, the generator will receive the outside option and leave the queue without completing the interconnection.

For $\tau < T$, the last step of the interconnection process is for a generator to decide whether to complete the interconnection after receiving the final cost estimate c. We assume that the total cost to bring the generator online, including the costs of construction and equipment, is $g(S_t, x) + c + \varepsilon_t$, where g represents how observed characteristics affect the cost, c is the interconnection cost from the final study, and ε_t is the generator specific unobserved cost. If the expected total profit exceeds the value of the outside option,

$$\pi(S_t, x) - g(S_t, x) - c - \varepsilon_t > b(t,x) + \xi_t,$$

the generator completes the interconnection. The unobservable of the outside option ξ_t is an i.i.d mean-zero random variable. The expected value of reaching this stage is

$$\Pi(t,x) = E_{\xi,\varepsilon} \max\left\{\pi(S_t, x) - g(S_t, x) - c - \varepsilon_t, b(t,x) + \xi_t\right\}, \tag{4}$$

We next consider the generator decision when it has two non-final studies. The decision is to whether to wait for the third study or withdraw. The option value of waiting depends on the probability of receiving a study next period, the waiting cost, and the value of the outside option. Given the current cost estimate c from the second study, the value of waiting is given by the following Bellman equation

$$\begin{aligned} W(c,z,\tau,\tilde{\tau},t,x) = E_\xi \max\Bigg\{ & b(t,x) + \xi_t, \sum_{c'} r(c'; c,z,\tau,\tilde{\tau},t,x) \cdot \Pi(t,x) \\ & + \left(1 - \sum_{c'} r(c'; c,z,\tau,\tilde{\tau},t,x)\right) \cdot W(c,z,\tau+1,\tilde{\tau}+1,t+1,x) - o(\tau,\tilde{\tau},t,x)\Bigg\}. \end{aligned} \tag{5}$$

where we take expectations over values of the outside options and the costs to be realized in the final study. We do not separately include a discount factor in addition to the waiting cost. The probability of staying in the queue is the probability that the first term in the maximand is lower than the second term. We also note that this formulation accounts for the fee to request the next study because the waiting cost $o(\tau, \tilde{\tau}, t, x)$ can vary with whether the current study is new ($\tilde{\tau} = 0$).

Now we consider the decision when the generator has a non-final first study, and decides whether to wait for the second study. The generator may receive a second study that is the final study, a second study that is not the final study, or withdraw. The value of waiting takes into account the respective payoffs:

$$V\left(c,z,\tau,\tilde{\tau},t,x\right)=E_{\xi}\max\left\{b\left(t,x\right)+\xi_{t},\sum_{c'}p\left(c';c,z,\tau,\tilde{\tau},t,x\right)\cdot\Pi\left(t,x\right)\right. \tag{6}$$

$$+\sum_{c',z'}q\left(c',z';c,z,\tau,\tilde{\tau},t,x\right)\cdot W\left(c',z',\tau+1,\tilde{\tau}+1,t+1,x\right)$$

$$+\left(1-\sum_{c'}p\left(c';c,z,\tau,\tilde{\tau},t,x\right)-\sum_{c',z'}q\left(c',z';c,z,\tau,\tilde{\tau},t,x\right)\right)$$

$$\left.\cdot V\left(c,z,\tau+1,\tilde{\tau}+1,t+1,x\right)-o\left(\tau,\tilde{\tau},t,x\right)\right\} \tag{7}$$

In the above, we can normalize the net mean profit π to be $\pi-g-b$. This normalization does not affect the choice probabilities of waiting or completion but simplifies the Bellman equations. With a slight abuse of notation, we write our Bellman equations as

$$\Pi\left(t,x\right)=E_{\xi,\varepsilon}\max\left\{\pi\left(t,x\right)-c-\varepsilon_{t},\xi_{t}\right\}, \tag{8}$$

$$W\left(c,z,\tau,\tilde{\tau},t,x\right)=E_{\xi}\max\left\{\xi_{t},\sum_{c'}r\left(c';c,z,\tau,\tilde{\tau},t,x\right)\cdot\Pi\left(t,x\right)\right.$$

$$\left.+\left(1-\sum_{c'}r\left(c';c,z,\tau,\tilde{\tau},t,x\right)\right)\cdot W\left(c,z,\tau+1,\tilde{\tau}+1,t+1,x\right)-o\left(\tau,\tilde{\tau},t,x\right)\right\}. \tag{9}$$

$$V\left(c,z,\tau,\tilde{\tau},t,x\right)=E_{\xi}\max\left\{\xi_{t},\sum_{c}p\left(c;c,z,\tau,\tilde{\tau},t,x\right)\cdot\Pi\left(t,x\right)+\sum_{c',z'}q\left(c',z';c,z,\tau,\tilde{\tau},t,x\right)\right.$$

$$\cdot W\left(c',z',\tau+1,\tilde{\tau}+1,t+1,x\right)+\left(1-\sum_{c'}p\left(c';c,z,\tau,\tilde{\tau},t,x\right)\right.$$

$$\left.\left.-\sum_{c',z'}q\left(c',z';c,z,\tau,\tilde{\tau},t,x\right)\right)\cdot V\left(c,z,\tau+1,\tilde{\tau}+1,t+1,x\right)-o\left(\tau,\tilde{\tau},t,x\right)\right\} \tag{10}$$

4.1.4 Queuing Equilibrium

We consider a finite-horizon queuing equilibrium, where the beliefs of the generators are consistent with the state of the queue in period t (calendar). The finite horizon assumption allows us to capture the non-stationarity in the costs of wind turbines and solar panels and the increase in the number of entrants. The equilibrium concept generalizes the equilibrium in Agarwal et al. (2021) to a non-steady-state setting.

We use $\mathit{\Psi}\left(c,t,x\right)$ to represent the withdrawal probability of a generator with a cost estimate c in the final study, $\mathit{\Lambda}\left(c,z,\tau,\tilde{\tau},t,x\right)$ to represent the withdrawal probability when it waits for the third study, and $\mathit{\Upsilon}\left(c,z,\tau,\tilde{\tau},t,x\right)$ to represent the withdrawal probability when it waits for the second study. The withdrawal probabilities $\left(\mathit{\Psi},\mathit{\Lambda},\mathit{\Upsilon}\right)$ are associated with the Bellman equations in (8), (9) and (10). We use $m_{t}\left(c,z,\tau,\tilde{\tau},k,x\right)$ to denote the fraction of generators waiting in period t with a cost estimate c, time-varying characteristics $\{z, \tau, \tilde{\tau}, k\}$, and time-invariant characteristics x. The equilibrium consists of (1) optimal withdrawal probabilities consistent with the Bellman equations, (2) the composition of the queue in every period $\{m_t\}_{t=1}^{T}$, and (3) the number of waiting generators N_t in every period $\{N_t\}_{t=1}^{T}$. We define the state of the queue to be

$$S_t = \left\{ \{m_t (c, z, \tau, \tilde{\tau}, k, x)\}_{c,z,\tau,\tilde{\tau},k,x}, N_t \right\}.$$

A queuing equilibrium satisfies the following conditions:

1. Optimality conditions. The withdrawal probabilities $(\Psi, \Lambda, \Upsilon)$ are consistent with the Bellman equations in (8), (9) and (10).
2. Consistent beliefs. The generators beliefs about the arrival probability of the next study and its contents are consistent with (2) and (3).
3. Balance conditions.
   (a) The transition of the queue ($\tau > 1$).
      i. For generators with two studies and waiting for the third study,

$$\begin{aligned} &N_{t+1} m_{t+1} (c, z, \tau + 1, \tilde{\tau} + 1, t + 1, k = 2, x) \\ &= N_t m_t (c, z, \tau, \tilde{\tau}, k = 2, x) \cdot (1 - \Lambda (c, \tilde{z}, \tau, \tilde{\tau}, t, x)) \\ &\cdot \left(1 - \sum_{c'} r (c'; c, z, \tau, \tilde{\tau}, t, x) \right) \end{aligned} \tag{11}$$

      ii. For generators just receiving the second study,

$$\begin{aligned} &N_{t+1} m_{t+1} (c, z, \tau + 1, 0, t + 1, k = 2, x) \\ &= N_t \sum_{c', z', \tilde{\tau}'} m_t (c', z', \tau, \tilde{\tau}', k = 1, x) \\ &\cdot (1 - \Upsilon (c', z', \tau, \tilde{\tau}', t, x)) \cdot q (c, z; c', z', \tau, \tilde{\tau}', t, x) . \end{aligned} \tag{12}$$

      iii. For generators with one study and waiting for the second study,

$$\begin{aligned} &N_{t+1} m_{t+1} (c, z, \tau + 1, t + 1, k = 1, x) \\ &= N_t m_t (c, z, \tau, \tilde{\tau}, k = 1, x) \cdot (1 - \Upsilon (c, z, \tau, \tilde{\tau}, t, x)) \\ &\cdot \left(1 - \sum_{c', z'} q (c', z'; c, z, \tau, \tilde{\tau}, t, x) - \sum_{c'} p (c'; c, z, \tau, \tilde{\tau}, t, x) \right) . \end{aligned} \tag{13}$$

   (b) The boundary condition (entry):

$$N_t m_t (c, z, \tau = 1, \tilde{\tau} = 0, k = 1, x) = n_t (c, z, x) , \tag{14}$$

where n_t is the number of new generators joining the queue in t with the first study cost estimate c and characteristics (z, x).

5 Identification and Estimation

There are two key sets of parameters to our model. First, we directly estimate from data the functions H_0, H_1 and H that govern how PJM issues studies. Second, we use the estimated functions to construct generators' beliefs and use the withdrawal and completion decisions to recover the generator preferences. A period in our model is a quarter. We assume that a generator can wait a maximum of 5 years (T =20 quarters).

5.1 Transition Dynamics

Below we describe each component of the transition probability functions. We also discuss key variables included in these functions. The detailed specifications of these functions are provided in Appendix C.1.

We first estimate the probability functions H_0, H_1, and H that describe the timing and information of a new study. These functions are akin to the exogenous state transitions in empirical applications of dynamic games, and are directly estimable from data (e.g., Aguirregabiria & Mira (2007), Bajari et al. (2007)).

These functions H_0, H_1, and H require the same set of inputs from the previous study. These inputs consist of the cost assessment c from the last study, the study information z, the time since the generator entered the queue τ, the time since the last study was issued $\tilde{\tau}$, the current calendar time t, the generator-specific characteristics x, and the current status of the queue S_t. The observable x includes characteristics that do not change over time, such as generator size, fuel type, and location. For the status of the queue, we include the total number and capacity of generators in the queue, as well as the number and capacity of nearby generators in the queue. For the nearby generators, we count up the number of generators in the queue within 10km and within 100km of the focal generator and the total capacity of these generators. This gives us three sets of measures that capture the limited processing ability at both the PJM system level and the local level.

The outputs of the functions H_0, H_1, and H differ. The functions H_0 and H generate the probability that a new study that is the final study (whether it is the second or third study) will be issued in the current period, and, conditional on a new study, the new cost c. The function H_1 generates the probability that a new study that is not the final study will be issued, and, conditional on a new study, the probability of a cost c and an update of the variables z. The new z informs how soon the next study arrives and what the final interconnection cost will be.

5.1.1 H Function

We start with H, the probability of receiving the third and final study conditional on having received the second study. We divide the interconnection costs (in million \$/MW) into $L = 5$ bins, with bin $\ell \in C_\ell = \{0, (0, 0.01], (0.01, 0.05], (0.05, 0.20], (0.20, \infty]\}$. We specify the latent variables governing study arrivals and costs as

$$y^{\star\text{arrive}} = \beta^{\text{arrive}} \cdot d_1(\ell, z, x, S_t), y^{\star\text{cost}} = \beta^{\text{cost}} \cdot d_2(\ell, z, x, S_t),$$

where the $d_{(\cdot)}(\cdot)$ functions are flexible polynomials of the characteristics, and the β's are vectors of parameters. Below we use ℓ in place c to make it clear that we model the cost as an ordinal discrete variable. For generators waiting for the third study, the probability that the new study arrives and that the new cost estimate is in bin ℓ' is defined as

$$H(\ell'; \ell, z, \tau, \tilde{\tau}, t, x, S_t) = \Pr\left(0 < y^{\star\text{arrive}} + \epsilon_{it}^{\text{arrive}}, \mu_{\ell'} \leq y^{\star\text{cost}} + \epsilon_{it}^{\text{cost}} \leq \mu_{\ell'+1}\right), \tag{15}$$

where $\mu_1 = -\infty, \mu_2 = 0$, and $\mu_2 \leq ... \leq \mu_L < \mu_{L+1} = \infty$ are a series of parameters. We allow the normally distributed errors $\epsilon_t^{\text{arrive}}$ and ϵ_t^{cost} to be correlated. The exact cost is a random draw from the empirical distribution of the observed interconnection costs for that cost bin.

5.1.2 H_1, H_0 and Initial Cost Distribution

For the probability function H_1, we also need to specify the probability that the second study is not the final study, and, in the event of a non-final second study, how the information from previous studies is updated. We specify the probability that the second study is the final study as a flexible probit function.

The information z revealed in the previous studies affects the probability of study arrivals and being in an interconnection cost bin. In particular, we track $z = (z_1, z_2)$, where $z_1 \in \{0, 1\}$ is whether a set of engineering tests has been performed, and $z_2 \in \{0, 1\}$ is whether PJM has determined the generator is part of a cost sharing cluster. For z_1, we focus on a set of three tests: generator deliverability, multiple facility contingency, and short circuit analysis. These tests are usually conducted together, and they study the ability of the transmission infrastructure to transmit power in a given geographical region. If PJM performs these tests in a study, the variable z_{1k} is set to 1 in all subsequent studies. These tests likely result in more certainty about the interconnection cost estimate.

The other information is whether the generator is in a cost-sharing cluster, z_2. To determine which generators are in the same cost-sharing cluster, PJM conducts additional tests (short circuit dynamic analysis and system protection analysis) to identify related generators. PJM makes this determination in the second study. We set $z_2 = 0$ when the generator has the first study and is waiting for the second study. If the second study is not final and shows that the generator is part of a cost-sharing cluster, z_2 is set to 1 as the generator awaits the third study. Being in a cost-sharing cluster may slow study arrivals.

These two characteristics are binary, as is whether the second study is the final study. We thus use three probit models for these outcomes. The respective outcomes are one if the new study has performed the tests, if the new study shows the generator is part of a cost-sharing cluster, and if the second study is not the final study. For simplicity, we additionally assume that their normal random unobservables are independent. Together, these probit models generate three probabilities, p^{test}, p^{cluster}, and p^{final}. We omit their arguments $(\ell, z, \tau, \tilde{\tau}, t, k, x, S_t)$ here to simplify notation.

We specify the H_1 function in two steps. First, we define the function

$$h\left(\ell'; \ell, z, \tau, \tilde{\tau}, t, k=2, x, S_t\right) = \Pr\left(0 < u^{\star\text{arrive}} + \zeta_{it}^{\text{arrive}}, v_{\ell'} \le u^{\star\text{cost}} + \zeta_{it}^{\text{cost}} \le v_{\ell'+1}\right), \tag{16}$$

For a generator waiting for the second study, $h(\cdot)$ generates the probability the study arrives and the corresponding cost bin. u, v, and ζ are defined analogously to y, μ, and ϵ in Equation (15).

The function H_1 is defined as the probability that a second and non-final study arrives with a cost in the ℓ'th bin, cluster status $y^{\text{cluster}} \in \{0,1\}$, and test status $y^{\text{test}} \in \{0,1\}$:

$$\begin{aligned} H_1 = &\left(y^{\text{cluster}} p^{\text{cluster}} + \left(1 - y^{\text{cluster}}\right)\left(1 - p^{\text{cluster}}\right)\right) \\ &\cdot \left(y^{\text{test}} p^{\text{test}} + \left(1 - y^{\text{test}}\right)\left(1 - p^{\text{test}}\right)\right) \cdot \left(1 - p^{\text{final}}\right) \cdot h. \end{aligned}$$

The probability that a second and final study arrives with the cost in bin ℓ' is

$$H_0 = p^{\text{final}} \cdot h.$$

Finally, we estimate the distribution of the costs in the first study. We use an ordered probit model for this cost. The probability of having a cost in bin ℓ is denoted as $H^{\text{init}}(\ell; x, S_t)$.

5.1.3 Identification and Estimation of the Transition Dynamics

The key identifying assumption is that any generator characteristics that drive the withdrawal decision but are not in $(c, z, \tau, \tilde{\tau}, k, t, S_t, x)$ are independent of the unobservables underlying the process of PJM issuing studies (the unobservables in the probit and the ordered-probit models above). We flexibly condition on a number of observables, and interviews with industry experts suggest that the additional motives for withdrawing a generator that we do not control for, e.g., a state or locality fails to pass a proposed loan program for solar generators, are largely unrelated to PJM's studies.

We use maximum likelihood to estimate the models. The full estimates are provided in Appendix C.1. In this section, we focus on the estimates of the study arrival probability. We do not find that PJM delivers the second study more slowly when the queue size is large, but this effect is prominent with the third study. In Table 5, we present the effect of increasing the queue size by 10% on the probability of receiving a third study.[10] The reported effects are average effects across each generator-quarter observation for generators requiring a third study in the sample. At the point estimates, an increase of 10% in the total queue size reduces the probability of receiving the third study by 10%. In Figure 4, we plot the confidence intervals for the effect of increasing the queue

[10] Specifically, we have six measures of queue size (number of generators and associated capacity in the queue overall, within 10km, and within 100km), and we increase all six by 10%.

size, for every generator-quarter combination waiting for the third study (sorted by the probability of receiving the third study). We do not find evidence that renewable generators receive studies more slowly than other generators.

Table 5: Marginal Effects of Increasing the Queue Sizes on Study 3 Arrival Probability

	Avg Arrival Prob	ΔPJM queue↑=10%,	
		$\Delta\,\mathrm{Pr}$ new study	$\Delta\,\mathrm{Pr}$ new study se
Renewable, $\leq$ 20MW	0.10	-0.008	0.004
Renewable, $>$ 20MW	0.07	-0.006	0.003
Non-Renewable, $\leq$ 20MW	0.11	-0.008	0.004
Non-Renewable, $>$ 20MW	0.09	-0.008	0.003

5.2 Generator Preferences

Using the estimated state transition functions H_0, H_1 and H above, we next estimate the determinants of the profit π, the waiting cost o and the distribution of the unobservable in the profit function ε_t. We take as given the first study cost and other information revealed in the first study.

5.2.1 Identification

As part of the normalization, we assume the value of the outside option ξ_t is a mean-zero i.i.d normal random variable with standard deviation σ. The key identifying variation is the interconnection cost in the PJM studies. Various trade publications and interviews with experts indicate that even industry veterans find the interconnection costs unpredictable. These costs are correlated across studies, but can also change significantly. We use the interconnection costs in various stages of the queue to identify both the profit function π and the waiting costs o.

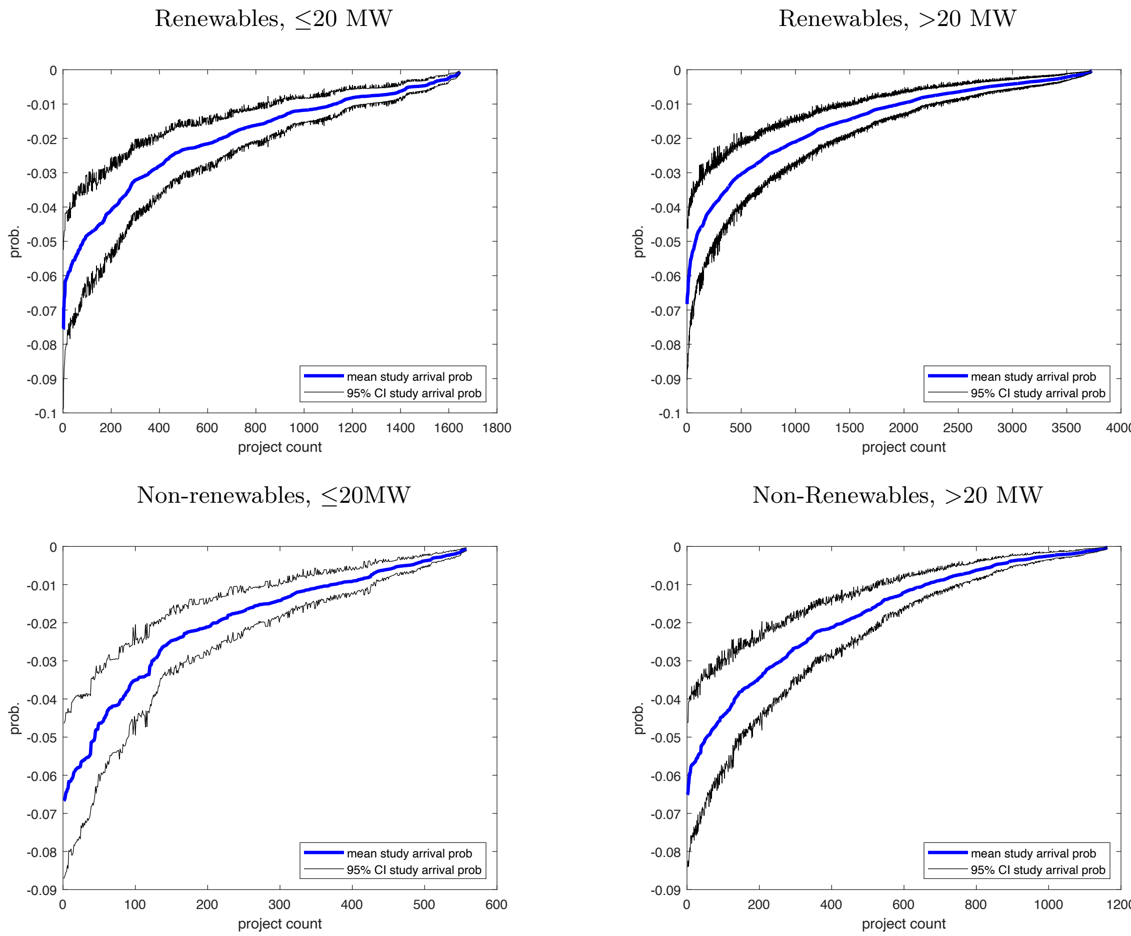
We start with the identification of the payoff function. In standard optimal stopping problems, it is often not possible to separately identify the waiting cost o and the payoff function π, because the a stopping decision (withdrawal) may be explained by a low payoff or a high waiting cost. Our case is different. We observe two types of decisions: the decision to wait while the generator is in the queue, and the decision to complete the interconnection when the final study is issued. Given the exogenous shifter of the cost c, the completion decision Ψ implied by the maximization problem in equation (8) directly identifies the payoff function following the standard identification argument of binary choice problems (Manski (1988)).

Given π, we can use backward induction to construct the value functions in (9) and (10). For example, the only unknown parameters in the choice probabilities Λ and Υ in the period $T-1$ are the waiting costs, and are identified by the variations of the second study interconnection costs. Applying the argument to period $T-2, \ldots, 1$ identifies the waiting cost in each period.

We further extend our model to include unobserved heterogeneity. Specifically, we specify

$$\pi_i\left(t, x\right) = \beta^{\pi} \cdot d_{\pi}\left(S_t, x\right) + \zeta_{\mathrm{sub}(i)},$$

Figure 4: Effect of Increasing the Queue Size on Third Study Arrival Probability: All Generator-Quarter Combinations Waiting for the Third Study



where β_π is a vector of parameters, $d_\pi(z_{it}, x_i)$ is a vector of flexible controls of generator characteristics that may vary over time, and the unobservable $\zeta_{\text{sub}(i)}$ is a substation random effect with a normal distribution and unknown variance σ_{sub}. The notation sub (i) indicates the nearest substation to the generator i. The random effect helps to capture persistent local unobservables. We can use the panel structure of the data, where multiple generators enter near the same substation, to identify σ_{sub}. The intuition is that a larger variance implies stronger within substation correlations in both the withdrawal decisions while generators wait in the queue and the completion decisions when the generators receive their final studies.

5.2.2 Estimation

We use a simulated maximum likelihood approach to recover generator preference parameters. We simulate $\zeta_{\text{sub}(i)}$ from a normal distribution to form the joint likelihood of completion and waiting for generators whose nearest substation is sub (i). We provide the details of the likelihood function in

Appendix C.2. For the vector of profit shifters d_π, we include fuel types, generator sizes, fixed effects for years in which the first studies are received, the calendar years, and various interactions. Table 6 reports select parameter estimates, and all estimates are reported in Appendix C.2. The profit π function is a linear index over a large number of generator characteristics and their interactions. We include persistent, normally distributed substation level heterogeneity, where each generator is associated with its nearest connecting substation. We allow the waiting cost to depend on the calendar year, generator characteristics, their interactions, and when the previous studies were issued. The waiting costs reflect the rents a generator must pay to hold the land and how much a developer values the study fees required by PJM to maintain its queue position. Although PJM has set fee schedules, these fees are partially refundable, and we estimate how generators perceive these costs directly, in the period in which they receive the studies and in the following period.

Table 6: Select Model Estimates (Million \$/MW)

In-Service Profit π		Unobservables Std.		Waiting Cost o	
Renewables	-0.29	Construction ε, pre-2013	0.81	Study 1 at t β_{o1}	0.03
	0.08		0.11		0.01
Queued 2013-2015	0.12	Construction ε, 2013-15	0.28	Study 1 at t, $\ln \text{cap}$ $\tilde{\beta}_{o1}$	-0.00
	0.04		0.04		0.00
Queued 2016-2018	0.17	Construction ε, 2016-18	0.45	Study 1 at $t-1$, β_{o2}	0.04
	0.07		0.07		0.01
Queued after 2018	0.39	Construction ε, post-2018	0.48	Study 1 at $t-1$, $\ln \text{cap}$ $\tilde{\beta}_{o2}$	-0.00
	0.09		0.06		0.00
Renewables, Queued 2013-2015	0.07	Outside option ξ	0.08	Study 2 at t β_{o3}	-0.02
	0.06		0.01		0.01
Renewables, Queued 2016-2018	0.03	Substation ζ	0.11	Study 2 at t, $\ln \text{cap}$ $\tilde{\beta}_{o3}$	-0.00
	0.10		0.02		0.00
Renewables, Queued after 2018	-0.02			Study 2 at $t-1$, β_{o4}	0.11
	0.11				0.01
				Study 2 at $t-1$, $\ln \text{cap}$ $\tilde{\beta}_{o4}$	-0.01
					0.00

The estimates reveal large observed and unobserved heterogeneities across fuel types and cohorts. Renewable generators value a megawatt of generating capacity on average 0.29 million less than fossil fuel generators. At the same time, generators in more recent years (post-2018) tend to have a higher expected payoff. This may reflect natural gas price decreases for natural gas generators and lower prices for panels and turbines for renewables.

Turning to the estimates of unobservable standard deviations, we find that the unobservable has a large effect when the generator decides whether to complete the interconnection, and the size of its effect changes over time. The standard deviation of the unobservable before 2013 is about 0.81 million dollars per megawatt, and it decreases to 0.48 million dollars per megawatt after 2018. As mentioned above, this unobservable likely captures the uncertainty of sourcing the components and actually building a generator, and both renewable and fossil fuel generators may face significant uncertainties: renewables may not be able to obtain the solar panels or wind turbines in time, a natural gas generator may need to apply for additional permits to build pipelines to transport fuel, or a project may simply fail to find a buyer for its power. In comparison, the quarter to quarter standard deviation of the unobserved outside option is smaller, about 0.08 million dollars per megawatt. The effect of the substation level heterogeneity is also limited, with a standard deviation of 0.11 million dollars per megawatt.

The waiting costs at t depends on waiting time since the last study was received, the calendar time, the generator's capacity and fuel type:

$$
\begin{aligned}
o = & \beta_o + \left(\beta_{o1} + \tilde{\beta}_{o1} \cdot \ln \text{cap}\right) \mathbb{1}\left(\tilde{\tau} = 0,\text{waits for 2nd study}\right) + \left(\beta_{o2} + \tilde{\beta}_{o2} \cdot \ln \text{cap}\right) \mathbb{1}\left(\tilde{\tau} = 1,\text{waits for 2nd study}\right) \\
& + \left(\beta_{o3} + \tilde{\beta}_{o3} \cdot \ln \text{cap}\right) \mathbb{1}\left(\tilde{\tau} = 0,\text{waits for 3rd study}\right) + \left(\beta_{o4} + \tilde{\beta}_{o4} \cdot \ln \text{cap}\right) \mathbb{1}\left(\tilde{\tau} = 1,\text{waits for 3rd study}\right) \\
& + \beta_{o5} \cdot \mathbb{1}\left(t \in [2013, 2015]\right) + \tilde{\beta}_{o5} \cdot \mathbb{1}\left(t \in [2013, 2015]\right) \cdot \mathbb{1}\left(\text{renewable}\right) \\
& + \beta_{o6} \cdot \mathbb{1}\left(t \in [2016, 2018]\right) + \tilde{\beta}_{o6} \cdot \mathbb{1}\left(t \in [2016, 2018]\right) \cdot \mathbb{1}\left(\text{renewable}\right) \\
& + \beta_{o7} \cdot \mathbb{1}\left(t \in [2018, \infty]\right) + \tilde{\beta}_{o7} \cdot \mathbb{1}\left(t \in [2018, \infty]\right) \cdot \mathbb{1}\left(\text{renewable}\right),
\end{aligned}
$$

where $\ln \text{cap}$ is the natural log of the capacity of the generator. The parameters β_{o1} through $\tilde{\beta}_{o4}$ capture the filing and other administrative costs to receive the next study.[11] Our estimates show that the per-megawatt cost to receive the second or third study is largely similar across generators of different sizes. The parameters β_{o5} through $\tilde{\beta}_{o7}$ measure the flow waiting costs dependent on time and fuel types. The estimates are generally small and insignificant (Table C.8 in Appendix C.1).

6 Equilibrium Simulation and Model Fit

We use the estimated model to simulate the queuing equilibrium defined in Section 4.1.4. The details of the simulation procedure are given in Appendix D. We provide a high level summary here.

1. For each generator i observed in the data, we start from its last period (T).[12]
   (a) Use the observed outcomes in the data to compute the queue status S_t for period $T, T-1, \ldots, 1$.
   (b) Compute the transition probabilities based on H_0, H_1 and H, and, in period 1, the probability of the initial cost falling in each bin ℓ based on H^{init}.
   (c) Solve the Bellman equations (8), (9) and (10), and the associated withdrawal probabilities.

[11] If the PJM does not require the third study, the generator does not pay for the costs associated with β_{o3} through $\tilde{\beta}_{o4}$. Similarly, if the PJM does not require the second study, the generator does not pay for the costs associated with β_{o1} through $\tilde{\beta}_{o4}$.

[12] The period T might corresponds with a calendar quarter that is outside our estimation sample. We assume the queue size grows at a constant quarterly rate of 3% between the end of the sample and the calendar time of a generator's T.

2. Given the initial strategy functions from step 1, the initial conditions from H^{init}, and the transition probabilities from H_0, H_1 and H, compute the fraction of generator i that withdraws, waits, and, if the final study arrives, completes the interconnection.[13] For each generator i, we track the fraction of the generator for each combination of (τ, z, ℓ).

3. Use the fraction of each generator in each state to update the queue. For example, to compute the total number of generators waiting in the queue in period t, we sum the fractions of generators that still wait in period t.

4. Use the updated status of the queue to recompute the initial conditions, the transition dynamics, and the new withdrawal probabilities. Use these new probabilities in Step 2 and iterate steps 2 through 4 until convergence.

The procedure embeds four assumptions. First, by explicitly starting the iteration with the observed outcomes, we select a particular equilibrium that is naturally motivated by data. Second, we assume perfect foresight for the evolution of the queue status. This is not an overly restrictive assumption, as in our context, it is not surprising that the queue sizes increase given the rapid decrease in the cost of renewable generators. At the same time, generators still perceive the arrival of the new studies, outside options, and the cost shock upon receiving the last study as random. In other words, in Equation (15), for example, a generator has perfect foresight over the evolution of $y^{\star\text{arrive}}$ and $y^{\star\text{cost}}$, but not over the events of arrivals or costs. Third, we take the time of entry and the characteristics x as given. Our discussion on speculative projects show that developers enter a large number of generators in the queue to ensure at least some of them have a low interconnection costs. Therefore the observed set of generators likely include the majority of potential entrants. Finally, to compute whether a generator benefits from a prior costly interconnection, we adopt a probabilistic interpretation of the fractions of generators in each state. We provide the details in Appendix B.1.

To validate our model, we compare the time series of aggregate investment it predicts to the data. Figure 5 shows the cumulative capacity that was completed, by queue year, for generators that entered the queue from 2013 to 2020.[14] The left panel shows the cumulative capacity for all generators, and the right panel shows the cumulative capacity for renewables. The solid black lines plot the total capacity of generators that are in service, i.e., they have completed construction and started operation. For example, the solid black line in 2018 represents the total in-service capacity, as of April 2022, of generators that entered the queue from 2013 to 2018. As we near the end of our sample, there are many generators that have received their final interconnection study but have not yet been placed in service or withdrawn from the queue. The dotted black lines represent the

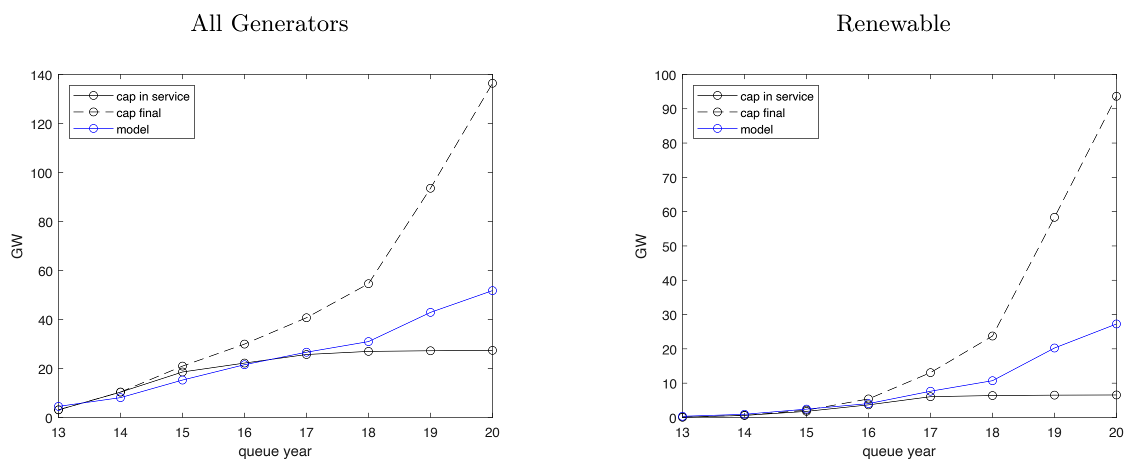
[13] For example, if the probability that the first study cost is zero is 0.3, the probability that the generator continues given the first cost is zero is 0.9, and the probability that the second study arrives in the first period is 0.05, the fraction of the generator i that has a first study cost of zero, waits in the second period, and does not have a second study is $0.3 \times 0.9 \times (1 - 0.05) = 0.26$.

[14] We focus on this more recent period because the proposed renewable capacity started to grow persistently and at an increasing speed in 2013. We compute the queuing equilibrium using our full sample of generators that queued from 2008-2020.

capacity of these generators (which include generators still under construction) plus the capacity of generators that are in service.

Our model is able to match these time series. The solid blue line plots the model's prediction for the total capacity *ever* placed in service, by queue year. For the early years, this should match the capacity actually placed in service as of April 2022 (the solid black line); all generators queued in these early years have had time to finish construction and begin operation. The model slightly under-predicts the in-service capacity for generators entering the queue in 2014 and 2015, but generally fits well. For later years, we expect the blue line to lie between the solid and dotted black lines, and it does.

Figure 5: Cumulative In-Service Capacity as of 2022, Model and Data



The solid black lines (cap in service) represent the total cumulative capacity of generators in our sample (post 2012) that have started operation by April 2022. For example, the capacity in 2018 represents the total capacity in service from generators that entered the queue from 2013-2018. The dotted black lines (cap final) represent this capacity plus the capacity of generators that have received their final study but not yet fully come online as of April 2022. The blue line is the simulated cumulative capacity that will ever be begin operation, by queue year.

7 Counterfactuals

We use the queuing equilibrium in Section 4.1.4 to compute the effects of alternative subsidy, cost-sharing, and queuing policies. We also decompose the direct and equilibrium effects of the policies.

7.1 Subsidizing Interconnection Costs

Our first set of counterfactuals considers direct subsidies. We consider four types of subsidies: (1) a uniform subsidy available to all projects, (2) a uniform subsidy available only to renewable projects, (3) subsidizing all interconnection costs by a fixed percentage, (4) subsidizing the interconnection costs of renewable generators by a fixed percentage. All subsidies are contingent on completion. One motivation for subsidies is to leverage the positive externalities between projects: a costly completion reduces costs for the next project. At the same time, rewarding completions encourages more projects to wait in the queue, and the larger queue may delay studies and increase withdrawals.

Figure 6 reports counterfactual investment under different subsidy policies. We compute both the total in-service capacity and the total cost of the subsidy for projects that queued from 2013 to 2020. The left panel focuses on subsidies that are applied to all projects, while the right panel shows results for subsidies that are available only to renewable generators. The purple lines show the effect of a uniform subsidy. The lowest subsidy level is \$0.01 million per MW, followed by \$0.05, \$0.10, ..., \$0.30 million per MW. The red lines represent the effects of percentage subsidies. We calculate the outcomes for subsidies of 10%, 20%, ..., 100%. . Finally, we report effects on both total capacity in service (solid lines) and renewable capacity in service (dotted lines).

We find that percentage subsidies outperform uniform subsidies on a per dollar basis. The left panel of Figure 6 shows that, for every level of total subsidy dollars, the red lines lie above the corresponding purple lines, indicating more investment under percentage subsidies. The main difference between the two forms of the subsidy is that a uniform subsidy subsidizes projects with 0 assessed interconnection costs. Thirty-five percent of the final studies in our data have an interconnection cost of zero. The marginal effect on completion of subsidizing these projects is less than the marginal effect of subsidizing projects with non-zero costs. This relationship is consistent with interconnection costs being difficult to predict so ex ante expected payoffs (exclusive of interconnection costs) are similar across projects with high and low interconnection costs.

Percentage subsidies also outperform uniform subsidies when the subsidy is only available to renewables (right panel). If the objective is to increase renewable energy investment, only offering the subsidy to renewables is considerably more cost effective; for example, one billion in percentage subsidy increases renewable investment by 4.5 GW, compared to 2.5 GW if the subsidy were available to all generators. Finally, offering a subsidy only to renewable generators increases total investment by less than it increases renewable investment. The subsidy causes more renewable generators to stay in the queue, thus delaying studies for non-renewable generators and causing more of them to withdraw.

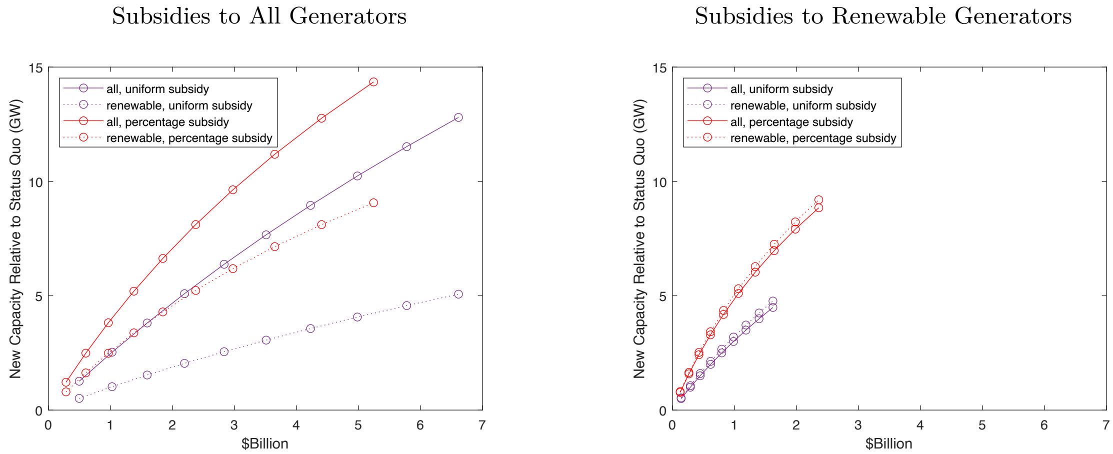
A further takeaway from this result is that the marginal subsidy dollar would likely be more effective if spent on interconnection costs rather than the solar Investment Tax Credit (ITC), a large federal subsidy. For most of our sample, the ITC was a thirty percent subsidy of the installation cost of the solar project. The ITC does not apply to the cost of interconnection (Sullivan 2017), a feature that makes it similar to our uniform subsidy.[15]

7.2 Cost Stabilization

One of the main complaints about the queuing process is that interconnection costs are difficult to predict. This uncertainty drives firms to enter more potential generators into the queue, generators

[15] While the ITC is a percentage subsidy, our uniform subsidy is on a per megawatt bassis, so it increases proportionally with project size. Project sizelikely explains much of the variation in installation costs: solar panels comprise most of this cost, and these panels are largely undifferentiated and traded globally.

Figure 6: Subsidizing Interconnection Costs



Left: subsidies to all generators. Purple solid line: the effect of uniform subsidies to all generators at the levels of \$0.01 million/MW, followed by \$0.05, \$0.10, ..., \$0.30 million/MW; for each point, the x value is the total subsidy and the y value is the added capacity of all generators. Dotted purple line: for each point, the x value is the subsidy spent on renewable generators (but all generators are still subsidized) and the y value is the added renewable capacity. Red line: the effect of subsidizing all interconnection costs by a fixed percentage, with the percentages of 10%, 20%, ..., 100%. Red dotted line:for each point, the x value is the subsidy spent on renewable generators (but all generators are still subsidized by the percentage subsidy) and the y value is the added renewable capacity.
Right: only renewables are subsidized. Purple solid line: the effect of a uniform subsidies to just renewable generators at the levels of \$0.01 million/MW, followed by \$0.05, \$0.10, ..., \$0.30 million/MW; for each point, the x value is the total subsidy and the y value is the added capacity of all generators. Dotted purple line: the x value is the uniform subsidy spent on renewable generators and the y value is the added renewable capacity. Red line: the effect of subsidizing renewable interconnection costs by a fixed percentage, with the percentages of 10%, 20%, ..., 100% on all generators; for each point, the x value is the total subsidy and the y value is the added capacity of all generators. Red dotted line: only the renewables are subsidized by a percentage subsidy, and for each point, the x value is the subsidy spent on renewable generators and the y value is the added renewable capacity.

with lower ex ante payoffs. Recent reforms target this uncertainty. They encourage transmission organizations to share costs across a larger number of generators, thus reducing instances where generators receive unexpectedly large costs.

We next consider a cost stabilization policy in which all generators are charged the same interconnection cost (per megawatt). A subsidy program will pay for the remainder of the costs if the total payment from the generators does not cover the total interconnection costs. A goal of PJM's reforms is to remove generators from the queue that are less ready to move forward. Thus, we expect fewer generators to enter the queue. We therefore simulate 9 scenarios, consisting of the combinations of three cost levels (\$0.01, 0.05 and 0.1 million per MW) and three levels of potential entrants (25%, 50% and 75% of the current number of potential entrants). The bottom percentiles of entrants are removed from the queue. For example, when the level of entry is set at 25%, we order generators by the per-megawatt expected value of being in the queue from the factual simulation in Section 6 (V with $\tau = 1$) and remove the bottom 75% of generators.

Table 7 reports the simulation effects. We report the change of total in-service capacity for generators queued in 2013 to 2020 relative to the status quo (factual simulation). The upper panel reports results for all generators, while the lower panel reports results for renewable generators. We find that if the entry level is high (75% and above), guaranteeing low costs (\$0.01 and \$0.05 million per MW) increases the overall capacity in service. Notably, even when just the top 50% generators remain in the queue and the cost is set at $0.10 million per MW, more renewable generators will complete. However, the per dollar effectiveness of the subsidy is lower than that of a direct subsidy program.

Table 7: Cost Stabilization and Entry Adjustment

All	Δ In-Service Capacities (GW)			
	Top 25%	Top 50%	Top 75%	All
0.01 m/MW	-24.53	-9.54	4.65	14.33
0.05 m/MW	-26.15	-12.33	0.08	8.15
0.10 m/MW	-28.28	-15.94	-5.64	0.69
Status Quo*	51.8 GW			
All	Subsidies ($ Billion)			
	Top 25%	Top 50%	Top 75%	All
0.01 m/MW	3.25	6.15	7.68	8.44
0.05 m/MW	2.04	4.19	5.06	5.38
0.10 m/MW	0.70	2.04	2.28	2.22
Renewable	Δ In-Service Capacities (GW)			
	Top 25%	Top 50%	Top 75%	All
0.01 m/MW	-5.2	5.59	8.64	9.57
0.05 m/MW	-6.44	3.53	6.25	7.01
0.10 m/MW	-8.08	0.84	3.13	3.72
Status Quo*	27.3 GW			
Renewable	Subsidies ($ Billion)			
	Top 25%	Top 50%	Top 75%	All
0.01 m/MW	2.95	5.46	6.21	6.36
0.05 m/MW	1.95	3.9	4.46	4.56
0.10 m/MW	0.84	2.16	2.55	2.60

*: Based on the simulation in Section 6.

We also note that equilibrium effects are important. For example, when the cost is guaranteed at $0.10 million per MW and 50% of the current generators enter the queue, the model predicts a 0.84 GW increase in renewable capacity after accounting for the equilibrium effects. If instead generators held the same beliefs as in the factual simulation in Section 6, the model predicts a decrease of 1.1 GW. The direct effect of the guaranteed cost is to decrease completion rates for generators with interconnection costs below it and increase completion rates for those with costs above it. In this example, the decrease in completion rates for generators with low or zero costs was more important and lead to a direct effect of less in-service capacity. But investment increases in equilibrium because the policy reduces the queue size. A shorter queue results in faster study delivery, and, in turn, higher completion rates.

7.3 Approximate Optimal Queuing Policy

The first two sets of counterfactual results show that both the cost of interconnection and the speed of study delivery can have a significant impact on the completion rate. At the same time, a planner can use a generator's characteristics to predict the probability of its completion. Therefore, an alternative queuing policy could use these predictions to prioritize some generators over others.

Suppose that, in a given period t, PJM may choose to consider a smaller set of generators than the full set of generators waiting in the queue. This reduces the effective queue size in the H functions. The generators not in this consideration set will receive a new study with probability 0. The generators in the consideration set will receive studies faster due to the reduced queue size. If the marginal effect on completion of reduced congestion is greater than the loss from excluding some generators, the policy will lead to more in-service capacity.

We consider the following simple implementation. Let $\rho(c,t,x)$ be the number of generators with characteristics x receiving the final cost estimate c in period t. This probability can be calculated recursively based on the H_0, H_1 and H distribution functions of transition dynamics and withdrawal probabilities Λ and Υ. We provide the details in Appendix B.2. Let θ represent a policy maker's preference for renewable capacity. Specifically, we search for a vector of weights $\boldsymbol{w} = (w_{xt_0})$ specific to each value of x and the time a generator enters the queue t_0, such that

$$\begin{aligned}&\max_{\boldsymbol{w}} \sum_{c,t,x} \left(\theta \cdot \mathbb{1}\left(i \text{ is renewable}\right) + (1-\theta) \cdot \mathbb{1}\left(i \text{ is not renewable}\right)\right) \\ &\cdot \rho(c,t,x) \cdot \Psi(c,t,x) \cdot \text{cap}_x,\end{aligned}$$

subject to the balance conditions

1. For generators with two studies and waiting for the third study,

$$\begin{aligned}&N_{t+1} m_{t+1}\left(c, z, \tau+1, \tilde{\tau}+1, t+1, k=2, x\right) \\ &= N_t m_t\left(c, z, \tau, \tilde{\tau}, k=2, x\right) \cdot \left(1 - \Lambda\left(c, \tilde{z}, \tau, \tilde{\tau}, t, x\right)\right) \\ &\cdot \left(1 - \sum_{c'} r\left(c'; c, z, \tau, \tilde{\tau}, t, x\right) w_{x,t-\tau}\right) \end{aligned} \tag{17}$$

2. For generators just receiving the second study,

$$\begin{aligned}
&N_{t+1}m_{t+1}\left(c,z,\tau+1,0,t+1,k=2,x\right)\\
&=N_t\sum_{c',z',\tilde{\tau}'}m_t\left(c',z',\tau,\tilde{\tau}',k=1,x\right)\\
&\cdot\left(1-\Upsilon\left(c',z',\tau,\tilde{\tau}',t,x\right)\right)\cdot q\left(c,z;c',z',\tau,\tilde{\tau}',t,x\right)\cdot w_{x,t-\tau}.
\end{aligned}\tag{18}$$

3. For generators with one study and waiting for the second study,

$$\begin{aligned}
&N_{t+1}m_{t+1}\left(c,z,\tau+1,t+1,k=1,x\right)\\
&=N_t m_t\left(c,z,\tau,\tilde{\tau},k=1,x\right)\cdot\left(1-\Upsilon\left(c,z,\tau,\tilde{\tau},t,x\right)\right)\\
&\cdot\left(1-\sum_{c',z'}q\left(c',z';c,z,\tau,\tilde{\tau},t,x\right)w_{x,t-\tau}-\sum_{c'}p\left(c';c,z,\tau,\tilde{\tau},t,x\right)w_{x,t-\tau}\right).
\end{aligned}\tag{19}$$

the boundary condition (14), and withdrawal probabilities consistent with the Bellman equations (8), (9) and (10), where the transition probabilities are modified as $r\cdot w$, $q\cdot w$, and $p\cdot w$ as above.

In this implementation, instead of being assigned different priorities over time, a generator has the same priority as other generators with the same x and entry time t_0 during its time in the queue. We do this for tractability reasons. For each combination of x and t_0, the optimization program chooses a number between 0 and 1, representing the share of generators in a specific group that will be included in the consideration set. Prioritization increases the delivery of studies. In theory, the weighting can be done at the individual generator level or even the generator-study level.

We find that, even with our limited flexibility of prioritizing at the group level, this policy would meaningfully increase generation capacity. In Figure 7, we plot the cumulative in-service capacity from 2013 to 2020. For this simulation, we set the weight the planner places on renewables θ to 0.55, so renewables are valued slightly more than other types of generation. With the approximate optimal queue, the increase in in-service capacity for renewables is about 2 GW, an 8% increase relative to the status quo. In Figure 7, we plot the time to final study for generators that complete the interconnection process. By selectively excluding small generators, the optimal weighting reduces the waiting time for the selected generators, especially for projects queuing in 2013 and 2014.

To maximize the in-service capacity, the optimization algorithm prioritizes large generators, and in particular, large renewable generators. The prioritization results in fewer but larger generators completed. In Figure 9, we show the results of this prioritization by plotting how the cumulative number of completed renewable generators changed and their average sizes. To calculate the average size for a given queue year, we divide the cumulative in-service capacity by the cumulative number of completed generators. We note that the completion rate for large renewable generators (>100MW) is 10.1%, still lower than the 18.7% of renewable generators at or below 20MW, but these large

Figure 7: Cumulative In-Service Capacities, 2013-2020

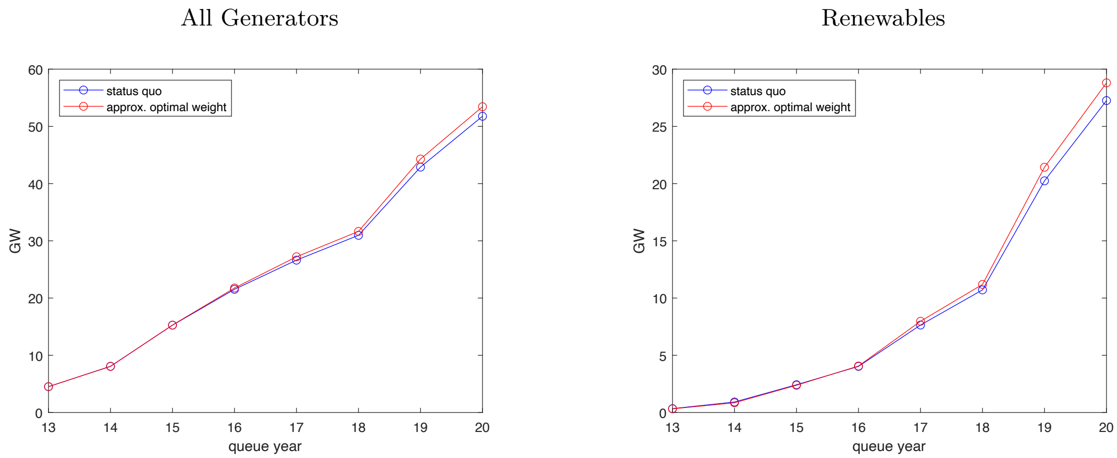
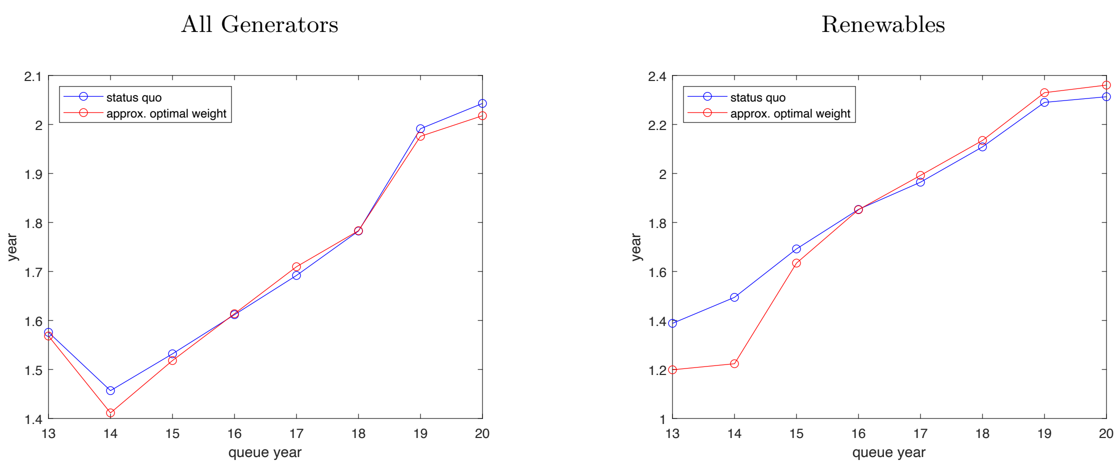


Figure 8: Time to Last Study Conditional on Completion (Years), 2013-2020



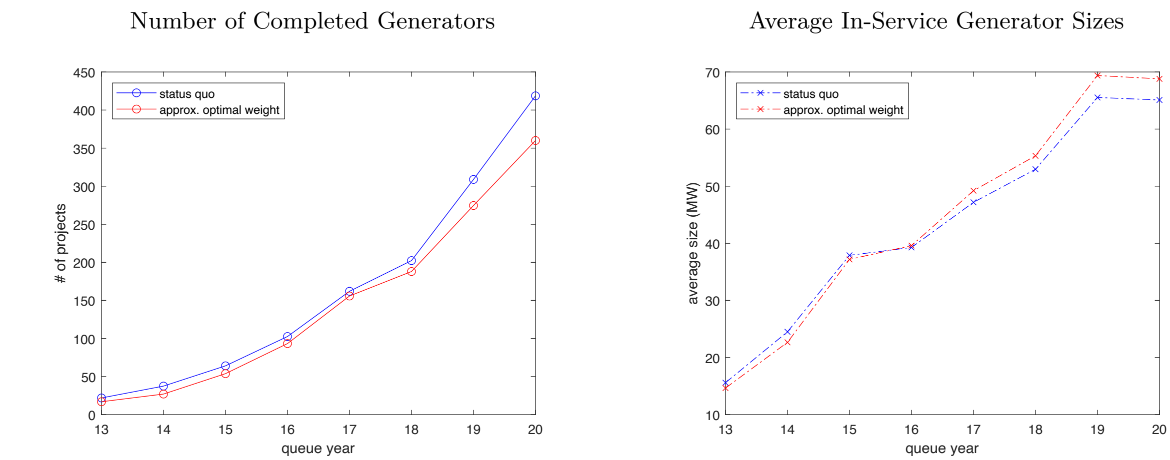
generators in expectation still result in more in-service renewable capacity.

8 Conclusion

We use novel data from the largest transmission operator in the United States to study the interconnection queue. These data show that interconnection costs are variable but can be very high. These costs are also higher on average for renewable generators. Less than a quarter of the generators that start the process complete it, and high interconnction costs are an important factor in explaining why generators withdraw from the queue.

We also show that there are important externalities across generators in the queue. Namely, as the queue size increases, generators in the queue must wait longer to receive their studies.

Figure 9: Cumulative Number of Completed Renewable Generators and Average Sizes, 2013-2020



Generators can also benefit from transmission infrastructure upgrades paid for by prior generators in the same location. These externalities imply that equilibrium effects are important in this setting.

We study policy reforms using a dynamic model that accounts for these equilibrium effects. We compare percentage subsidies for interconnection costs to uniform subsidies, and find that percentage subsidies are more effective at increasing the amount of generation capacity completed. An implication is that, for promoting renewable energy, the marginal dollar spent subsidizing interconnection costs is likely more effective than the marginal dollar spent subsidizing project construction. We also find that pre-committing to a level of interconnection costs to reduce uncertainty requires a significant subsidy to increase completion rates. Finally, we show that selectively prioritizing some generators based on observable characteristics can increase the amount of capacity completed by reducing wait times.

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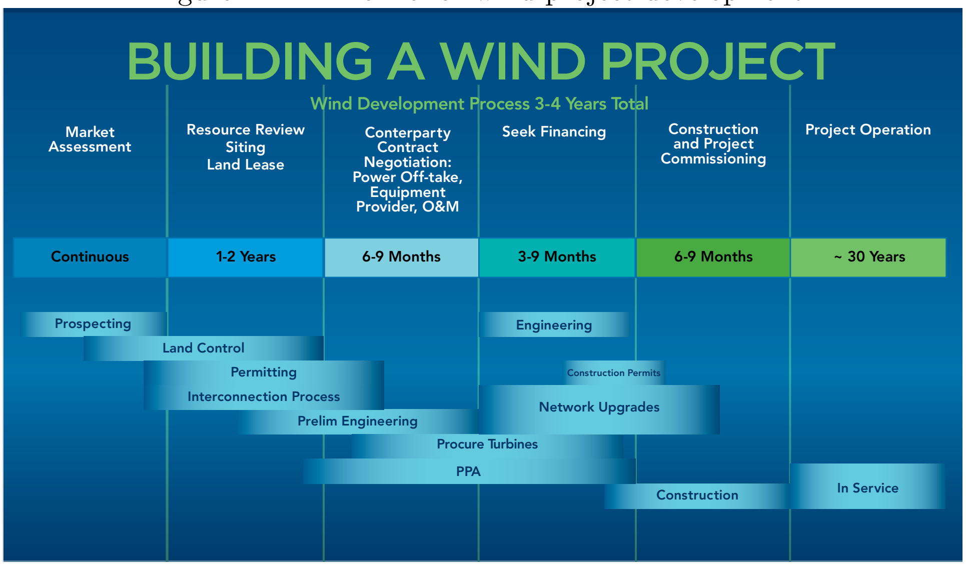
A Additional Figures and Tables

Figure A.1: Timeline for wind project development



Reproduced exactly from AWEA (2019), pg. 72.

B Calculation Details

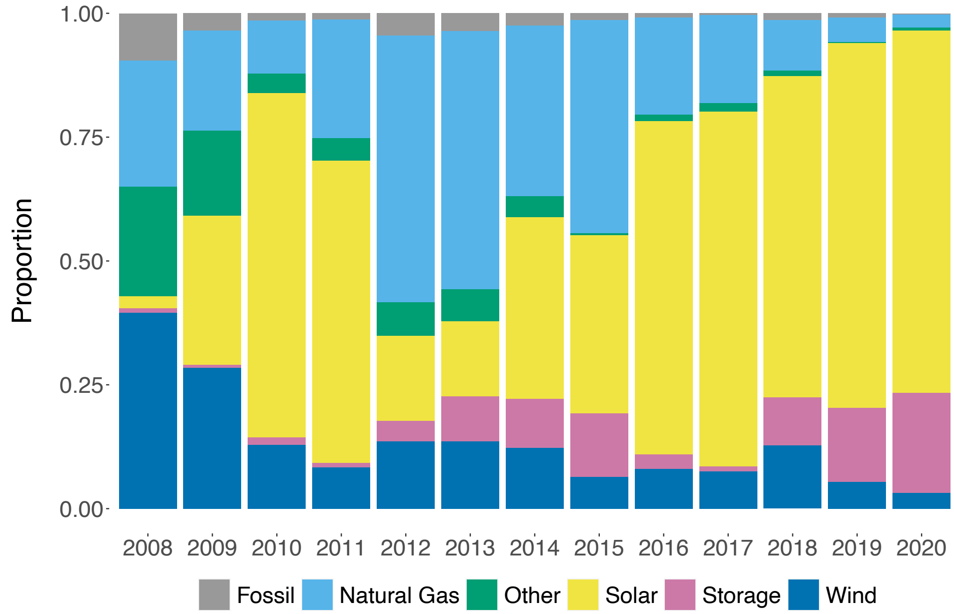
B.1 Calculating the Probability of Having a Costly Prior Interconnection

Suppose the number of costly generators that completed interconnection at substation j and within 10km of generator i are $n_t, n_{t-1}, n_{t-2}, \ldots$ in periods $t, t-1, \ldots$. The number of zero-cost generators in these periods are $\tilde{n}_t, \tilde{n}_{t-1}, \ldots$. The number of generators should be understood as the sum of relevant fractions. We interpret n as a probability whenever it is less than 1, and assume the probability is 1 if it is greater than 1. Denote these probabilities as ϖ and $\tilde{\varpi}$. Then we assume that probability that generator i faces a costly prior interconnection is

$$
\begin{aligned}
\varsigma =& \varpi_t \left(1-\tilde{\varpi}_t\right) + \left(1-\varpi_t\right)\left(1-\tilde{\varpi}_t\right)\varpi_{t-1}\left(1-\tilde{\varpi}_{t-1}\right) \\
&+ \left(1-\varpi_t\right)\left(1-\tilde{\varpi}_t\right)\left(1-\varpi_{t-1}\right)\left(1-\tilde{\varpi}_{t-1}\right)\varpi_{t-2}\left(1-\tilde{\varpi}_{t-2}\right) \\
&+ \cdots
\end{aligned}
$$

The probability functions H_0, H_1, and H that govern transition dynamics and the initial cost distribution function H^{init} use as input whether a generator faces a prior costly interconnection. We can calculate the probability, for example, either as $H_0(\varsigma)$, or as the weighted sum $(1-\varsigma)H_0(0) + \varsigma H_0(1)$. The difference from the two representations is small in our empirical application.

Figure A.2: Fuel type of generators entering the queue



Proportion of new generator interconnection requests by fuel type. Fossil is coal, oil, and diesel; other is biomass, nuclear, hydro, and wood.

B.2 Calculating $\rho(c,t,x)$

We use $\rho^{\star}(c,z,\tau,t_0,x)$ to denote the number of generators with a first study cost c and study information z, the first study but not any other study at the beginning of its waiting period τ, entry time of t_0, and time-invariant characteristics x. Then we have

$$
\begin{aligned}
&\rho^{\star}(c_1,z_1,\tau=0,t_0,x) = n_{t_0}(c_1,z_1,x),\\
&\rho^{\star}(c_1,z_1,\tau=1,t_0,x) = \rho_i^{\star}(c_1,z_1,\tau=0,t_0,x)\cdot\left(1-\Upsilon(c_1,z_1,\tau=1,\tilde{\tau}=0,t_0+1,x)\right)\\
&\cdot\left(1-\sum_{c_2} p(c_2;c_1,z_1,\tau=1,\tilde{\tau}=0,t_0+1,x) - \sum_{c_2,z_2} q(c_2,z_2;c_1,z_1,\tau=1,\tilde{\tau}=0,t_0+1,x)\right),\\
\\
&\rho^{\star}(c_1,z_1,\tau=2,t_0,x) = \rho_i^{\star}(c_1,z_1,\tau=1,t_0,x)\cdot\left(1-\Upsilon(c_1,z_1,\tau=2,\tilde{\tau}=1,t_0+2,x)\right)\\
&\cdot\left(1-\sum_{c_2} p(c_2;c_1,z_1,\tau=2,\tilde{\tau}=1,t_0+2,x) - \sum_{c_2,z_2} q(c_2,z_2;c_1,z_1,\tau=2,\tilde{\tau}=1,t_0+2,x)\right),\\
&\ldots
\end{aligned}
$$

We use $\rho^{\star\star}(c_2,z_2,\tau,\tilde{\tau},t_0,x)$ to denote the number of generators with two studies, the second study cost c_2, and characteristics z_2, waiting for the final study at the beginning of the period when it has waited τ periods and has had the second study for $\tilde{\tau}$ periods. Then

$$\rho^{\star\star}(c_2, z_2, \tau = 1, t_0, x) = 0,$$

$$\rho^{\star\star}(c_2, z_2, \tau = 2, \tilde{\tau} = 0, t_0, x) = \sum_{c_1, z_1} (1 - \varUpsilon(c_1, z_1, x))\, q(c_2, z_2; c_1, z_1, \tau = 1, \tilde{\tau} = 0, t_0 + 1, x),$$

$$\ldots$$

$$\rho^{\star\star}(c_2, z_2, \tau = 3, \tilde{\tau} = 0, t_0, x) = \sum_{c_1, z_1} \rho^{\star}(c_1, z_1, \tau = 2, t_0, x) \cdot (1 - \varUpsilon(c_1, z_1, \tau = 2, \tilde{\tau} = 1, t_0 + 2, x))$$

$$\cdot\, q(c_2, z_2; c_1, z_1, \tau = 2, \tilde{\tau} = 1, t_0 + 2, x),$$

$$\rho^{\star\star}(c_2, z_2, \tau = 3, \tilde{\tau} = 1, t_0, x) = \rho^{\star\star}(c_2, z_2, \tau = 2, \tilde{\tau} = 0, t_0, x) \cdot (1 - \varLambda(c_2, z_2, \tau = 2, \tilde{\tau} = 0, t_0 + 2, x))$$

$$\cdot \left(1 - \sum_{c_3} r(c_3; c_2, z_2, \tau = 2, \tilde{\tau} = 0, t_0 + 2, x)\right),$$

$$\ldots$$

The number of generators with characteristics x, a final study cost c in period t is

$$\begin{aligned}\rho(c, t, x) = \sum_{t_0, \tau} \mathbb{1}(t_0 + \tau = t) \cdot \sum_{c_1, z_1} \rho^{\star}(c_1, z_1, \tau, t_0, x) \\ \cdot (1 - \varUpsilon(c_1, z_1, \tau, \tau - 1, t, x)) \cdot p(c; c_1, z_1, \tau, \tau - 1, t, x) \\ + \sum_{c_2, z_2} \sum_{\tilde{\tau}=0}^{\tau-1} \rho^{\star\star}(c_2, z_2, \tau, \tilde{\tau}, t_0, x) \cdot (1 - \varLambda(c_2, z_2, \tau, \tilde{\tau}, t, x)) \cdot r(c; c_2, z_2, \tau, \tilde{\tau}, t, x)\Bigg).\end{aligned}$$

C Full Model Estimates

C.1 Transition dynamics

We first estimate the function $h(\ell'; \ell, z, \tau, \tilde{\tau}, t, k, x, S_t)$ in Equation (16). We directly include as covariates the indicator variable for whether the generator is waiting for the third study and its interaction with other covariates, so that this h function can also be used as H in Equation (15). We report the model estimates in Table C.1 and C.2.

The next three tables (C.2 through C.5) report the probit results for the outcomes of being in a cluster, being tested, and receiving a final cost estimate in the second study. Finally, we present the estimates of $H^{\text{init}}(S_t, x)$ in Table C.6.

C.2 Generator Preference

We present the full model estimates of the in-service profit function π in Table C.7. We present the full model estimates of the waiting cost function in Table C.8.

D Equilibrium Simulation

Fix a set of generators $\mathcal{I}$. We use the set of all observed generators. Each generator i is associated with a queue date t_i. Each generator receives the first study in $t_i + 1$. In the periods $t_i + 1$, $t_i + 2$, $\ldots, t_i + T$, if the generator has not received the final study, the generator decides whether to wait or continue. At the end of $t_i + T$, if the generator has not received the final study, the generator leaves the queue.

In the simulation, we solve for a vector of values $n_i(\ell, z, \tau, \tilde{\tau}, k)$, which is the fraction of generator i with a cost estimate in bin ℓ, study information z, having waited τ periods, $\tilde{\tau}$ periods from the last study, and waiting for kth study. In our solution, $n_i(\ell, z, \tau, \tilde{\tau}, k) \in [0, 1]$ is a fraction. In particular, we track $z = (z_1, z_2)$, where z_1 stands for whether a set of engineering tests has been performed, and z_2 is for whether PJM has determined a generator is part of a cost sharing cluster. Both variables are binary indicators. We focus on the tests of generator deliverability, multiple facility contingency and short circuit analysis. These tests are focused on the ability of the transmission infrastructure to transmit power in a given geographical region and in most cases conducted together. If PJM performs these tests in a study, the variable z_1 is set to 1 in all subsequent studies. To determine which generators are in the same cost-sharing cluster, the PJM conducts additional tests (short circuit dynamic analysis and system protection analysis) to identify related generators. We do not explicitly model this process. Instead, we assume the probability that a generator is assigned to be part of a cost-sharing cluster is a flexible profit function of local capacities. To limit computational burden, we only track whether the last study is received in the current period ($\tilde{\tau} = 0$), in the last period $\tilde{\tau} = 1$, or earlier ($\tilde{\tau} = \infty$).

1. Start with an initial guess of $n_i(\ell, z, \tau, \tilde{\tau}, k)$, where ℓ indicates the ℓth cost bin. We use the observed data as the starting point. For example, if a generator i with cost $c \in C_\ell$, and first study information z waited 2 periods and exited the queue, then $n_i(\ell, z, 1, 0, 2) = 1$, $n_i(\ell, z, 2, 1, 2) = 1$, and 0 for any other input values.

2. Use the initial guess, compute the state transition probabilities. The queue size at the calendar time t, for example, is calculated as

$$\sum_k \sum_{\tilde{\tau}} \sum_{\tau} \sum_{\ell} \sum_z \sum_i n_i(\ell, z, \tau, \tilde{\tau}, k) \, \mathbb{1}(t_i + \tau = t).$$

   Other queue level statistics can be calculated similarly.

3. Use the transition probabilities to solve the Bellman equations and the corresponding strategies Υ, Λ, and Ψ for each combination of $(\ell, z, \tau, \tilde{\tau}, k)$.

4. Use the transition probabilities to update n_i. Specifically, for those with two studies and

waiting for the third study and for any ℓ and z,

$$
\begin{aligned}
& n_i(\ell, z, \tau+1, \tilde{\tau}+1, t+1, k=3, x) \\
& = n_i(\ell, z, \tau, \tilde{\tau}, t, k=3, x) \cdot (1 - \Lambda(\ell, z, \tau, , \tilde{\tau}, t, k=3, x)) \\
& \cdot \left(1 - \sum_{\ell'} r(\ell'; c, z, x, \tau, \tilde{\tau}, t)\right)
\end{aligned}
$$

if $\tilde{\tau} \geq 0$, and

$$
\begin{aligned}
& n_i(\ell, z, \tau+1, 0, t+1, k=3, x) \\
& = \sum_{\ell', z', \tilde{\tau}'} n_i(\ell', z', \tau, \tilde{\tau}', t, k=2, x) \\
& \cdot (1 - \Upsilon(\ell', z', \tau, \tilde{\tau}', t, x)) \cdot q(\ell, z; \ell', z', x, \tau, \tilde{\tau}', t)
\end{aligned}
$$

For those with one study and waiting for the second study and for any ℓ and z,

$$
\begin{aligned}
& n_i(\ell, z, \tau+1, \tilde{\tau}+1, t+1, k=2, x) \\
& = n_i(\ell, z, \tau, \tilde{\tau}, t, k=2, x) \cdot (1 - \Upsilon(\ell, z, \tau, \tilde{\tau}, t, k=2, x)) \\
& \cdot \left(1 - \sum_{\ell', z'} q(\ell', z'; \ell, z, x, \tau, \tilde{\tau}, t) - \sum_{\ell'} p(\ell'; \ell, z, x, \tau, \tilde{\tau}, t)\right).
\end{aligned}
$$

5. Use the function $H^{\text{init}}(\ell; x_i, S_{t_i})$ to determine the fraction of i whose first study cost falls into bin ℓ when it enters the queue at t_i: $n_i(\ell, z, \tau=1, \tilde{\tau}=0, k=1) = H^{\text{init}}(\ell; x_i, S_{t_i})$. We assume the entry time t_i and the first study characteristics $z = z_i$ are fixed as observed in the data.

6. Use the updated queue to calculate the queue level statistics and repeat steps 2-5 until convergence.

Table A.1: Predictors of Interconnection Costs

	Log of (Study Cost/MW+1) (1)	Low Study Cost (2)
Project Size Bin 1 (10MW, 20MW]	-0.072***	0.002
	(0.024)	(0.031)
Project Size Bin 2 (20MW, 100MW]	-0.056**	-0.187***
	(0.025)	(0.032)
Project Size Bin 3 (100MW, 500MW]	-0.048*	-0.317***
	(0.026)	(0.034)
Project Size Bin 4 >500MW	-0.061**	-0.542***
	(0.026)	(0.053)
Distance To Substation:	0.006*	0.003
	(0.003)	(0.006)
Ordinance	0.026*	-0.082***
	(0.015)	(0.026)
Fuel-Natural Gas	-0.015	0.023
	(0.053)	(0.085)
Fuel-Solar	0.031	-0.549***
	(0.052)	(0.082)
Fuel-Wind	0.015	-0.319***
	(0.055)	(0.088)
Fuel-Storage	0.028	-0.334***
	(0.054)	(0.087)
Fuel-Other	0.004	0.025
	(0.060)	(0.106)
Prior RTEP Investment (0m, 60m]	0.012	0.018
	(0.016)	(0.022)
Prior RTEP Investment >60m	0.013	0.048**
	(0.014)	(0.024)
Observations	2,089	2,329
R-Squared	0.131	0.265

Projects queuing from 2008-2020. SEs in parentheses; clustered by substation. In column (1), Dep. var. is log of Study 2 interconnection cost estimates plus 1 (mean 0.14). In column (2), Dep. var. is indicator for Study 2 cost estimate less than 0.01m/MW (mean 0.30). Prior RTEP Investments is measured as investments made within 5 years of the issue date of a focal project and located within 10km of it. Controls for state and project queue year.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Summary Statistics for Cost Externality Regressions

	Study 1		Study 2	
	Mean	Std. Dev.	Mean	Std. Dev.
Cost/MW $<$ 0.01m	0.43	0.49	0.34	0.47
Prior cost $>$ 0.1m	0.09	0.29	0.10	0.29
Prior cost (0.1m, 0.5m]	0.03	0.18	0.03	0.16
Prior cost (0.5m, 3m]	0.03	0.17	0.03	0.17
Prior cost $>$ 3m	0.03	0.18	0.04	0.20
Two interconnections ago	0.04	0.20	0.05	0.22
Size (MW)	102	203	115	205
Log of (Size + 1)	3.53	1.49	3.84	1.35
Coal, Oil, Diesel	0.01	0.10	0.01	0.09
Natural Gas	0.16	0.37	0.17	0.38
Wind	0.07	0.26	0.08	0.28
Solar	0.62	0.49	0.60	0.49
Battery	0.04	0.19	0.04	0.19
Other	0.09	0.29	0.10	0.30
N	2,828		1,572	

Projects queuing from 2011-2020 (prior completions from 2008-2020).

Table C.1: H, h Functions: $y^{\star\text{arrival}}$

IL	-0.41	Renewables	0.17	Has waited>1 year	-0.31
	0.05		0.04		0.04
IN	-0.07	lnsize	-0.02	Has waited>1 year, wait for third study	0.51
	0.06		0.01		0.07
MD	0.12	size>100MW	-0.07	Has waited>2 years	0.07
	0.05		0.04		0.05
NJ	0.21	size>500MW	0.05	Has waited>2 years, wait for third study	0.30
	0.05		0.04		0.05
OH	-0.03	Renewables$\times\mathbb{1}\,(\text{size} > 100)$	0.02	Has waited>3 years	-0.13
	0.04		0.04		0.05
PA	0.14	in cluster	-0.18	Has waited>3 years, wait for third study	0.11
	0.04		0.06		0.06
VA	0.03	Year>2020	0.04	$\ln(\#\text{ proj in PJM queue})/10$	1.83
	0.04		0.02		0.31
WV	0.03	Wait for third study, queued in 2012-2015	-0.03	$\ln(\#\text{ proj in PJM queue})/10$	-4.89
	0.08		0.05	$\times\mathbb{1}\,(\text{wait for third study})$	0.41
cost0-0.01	-0.16	Queued in 2012-2015	0.15	Const.	-1.90
	0.03		0.04		0.16
cost0.01-0.05	-0.28	Renewables$\times\mathbb{1}\,(\text{queued in 2012-2015})$	0.04		
	0.03		0.04		
cost0.05-0.2	-0.49	(Queue year-2008)/10	-2.18		
	0.03		0.18		
cost>0.2	-0.69	(Year-2008)/10	1.96		
	0.04		0.18		

Table C.2: H, h Functions: $y^{\star\text{cost}}$

IL	-0.43	Renewables	0.44	corr($\epsilon^{\text{arrival}}, \epsilon^{\text{cost}}$)	0.98
	0.06		0.04		0.00
IN	-0.13	lnsize	0.05	Const	-1.79
	0.08		0.01		0.14
MD	0.22	Wait for third study	-0.09		
	0.06		0.09		
NJ	0.34	has test	-0.04		
	0.05		0.02		
OH	-0.16	in cluster	-0.14		
	0.05		0.08		
PA	0.18	Prior Costly Interconnection	0.07		
	0.05		0.06		
VA	-0.03	total RTEP>0	-0.03		
	0.05		0.02		
WV	0.04	yr>2016	0.02		
	0.11		0.03		
cost0-0.01	-0.09	# generators in the queue within	0.06		
	0.09	100 km	0.02		
cost0.01-0.05	-0.35	μ_2	0.19		
	0.10		0.01		
cost0.05-0.2	-0.19	μ_3	0.33		
	0.08		0.04		
cost>0.2	-0.17	μ_4	0.56		
	0.07		0.07		

Table C.3: Probit: Prob. of Being in a Cluster

IL	-0.42	Renewables	-0.40
	0.20		0.09
IN	-0.07	lnsize	0.11
	0.23		0.05
MD	-0.42	Wait for third study	0.00
	0.17		0.00
NJ	-0.51	has test	0.31
	0.17		0.12
OH	-0.54	Queued in 2019	1.07
	0.16		0.12
PA	0.19	Queued in 2020	2.15
	0.15		0.19
VA	0.10	Queued after 2020	2.91
	0.15		0.38
WV	0.05	Year>2016	0.43
	0.26		0.10
cost0-0.01	0.18	Waited>1 year	-0.13
	0.14		0.09
cost0.01-0.05	0.30	Waited>2 years	0.01
	0.11		0.12
cost0.05-0.2	0.47	Const	-2.15
	0.11		0.38
cost>0.2	-0.18		
	0.15		

Table C.4: Probit: Prob. of Being Given the Tests

IL	-0.13	Renewables	0.79
	0.40		0.22
IN	0.01	lnsize	0.01
	0.44		0.09
MD	1.00	Queued in 2019	1.92
	0.42		0.49
NJ	1.13	Queued in 2020	-1.77
	0.39		0.54
OH	-0.41	Queued after 2020	2.91
	0.36		0.38
PA	0.45	Year>2016	-0.59
	0.35		0.23
VA	-0.09	Waited>1 year	0.40
	0.45		0.24
WV	0.18	Waited>2 years	0.46
	0.46		0.31
cost0-0.01	-0.55	Const	-2.15
	0.34		0.38
cost0.01-0.05	-0.99		
	0.29		
cost0.05-0.2	-1.22		
	0.31		
cost>0.2	-0.22		
	0.31		

Table C.5: Probit: Prob. of Second Study Being the Final Study

IL	-0.54	Renewables	-0.08	Queued in 2012	0.
	0.27		0.34		0.
IN	-0.33	Renewables, Queued in 2012-2015	0.42	Queued in 2013	0.
	0.46		0.42		0.
MD	-0.27	Renewables, Queued in 2012-2015, size>40MW	4.37	Queued in 2014	0.
	0.23		3.50		0.
NJ	0.29	Renewables, Queued in 2016-2018	-0.22	Queued in 2015	0.
	0.22		0.40		0.
OH	-0.14	Renewables, Queued in 2016-2018, size>40MW	4.21	Queued in 2016	0.
	0.24		3.51		0.
PA	-0.14	Renewables, Queued after 2018	0.91	Queued after 2019, Wait time≤1 year	-1.
	0.21		0.39		0.
VA	0.09	Renewables, Queued in 2016-2018, size>40MW	9.93	ln (# proj in the queue within 10km)	0.
	0.22		3.35		0.
WV	0.46	Renewables, size>40MW	-5.71	ln (# proj in the queue within 100km)	-0.
	0.30		3.48		0.
cost0-0.01	-0.15	has test	-0.65	ln (total cap: proj in the queue within 10km)	-0.
	0.20		0.14		0.
cost0.01-0.05	-0.42	Waited>1 year	0.05	ln (total cap: proj in the queue within 100km)	0.
	0.15		0.46		0.
cost0.05-0.2	-0.94	Waited>2 years	-0.43	Const.	2.
	0.14		0.50		0.
cost>0.2	-1.66	Queued in 2012-2015, , size>40MW	0.16		
	0.17		0.56		
ln size	-0.20	Queued in 2016-2018, size>40MW	0.56		
	0.04		0.58		
size>40	0.06	Queued after 2018, size>40MW	-5.94		
	0.53		5.07		

Table C.6: H^{init}

IL	-0.28	Year >2020	-0.27	μ_2	0.31
	0.13		0.13		0.01
IN	-0.19	Renewables, Year 2013-2015	0.23	μ_3	0.93
	0.18		0.13		0.02
MD	0.40	Renewables, Year 2016-2018	-0.10	μ_4	1.98
	0.10		0.11		0.03
NJ	0.63	Renewables, Year >2018	0.41	Const	0.34
	0.10		20.36		0.19
OH	-0.09	Renewables, Year 2019	0.15		
	0.11		20.36		
PA	0.12	Renewables, Year 2020	-0.25		
	0.10		20.37		
VA	-0.23	Renewables, Year >2020	-0.04		
	0.10		20.37		
WV	-0.16	Renewables	0.62		
	0.17		0.07		
Year 2013-2015	-0.10	ln size	0.09		
	0.09		0.01		
Year 2016-2018	-0.01	ln (# proj in the queue within 100km)	0.15		
	0.09		0.03		
Year 2019	-0.54	ln (total cap: proj in the queue within 100km)	-0.12		
	0.17		0.03		
Year 2020	-0.25	Prior Costly Interconnection	-0.31		
	0.12		0.07		

Table C.7: Full Model Estimates: In-service Profit π

IL	-0.01	Renewables	-0.29	Year 2013-2015	0.08
	0.04		0.08		0.10
IN	-0.01	Renewables DE IL IN KY MD NC VA	0.00	Year 2013-2015 $\times \mathbb{1}$ (size $>$ 40)	0.03
	0.04		0.02		0.05
MD	-0.04	Renewables queued after 2018	-0.02	Year 2016-2018	-0.06
	0.03		0.11		0.11
NJ	-0.01	Is Renewable$\times$ lnsize	0.01	Year 2013-2015 $\times \mathbb{1}$ (size $>$ 40)	0.08
	0.03		0.01		0.06
OH	-0.03	Is Renewable$\times \mathbb{1}$ (size $>$ 40)	-0.08	Year>2018	-0.17
	0.03		0.13		0.13
PA	-0.03	Is Renewable$\times \mathbb{1}$ (size $>$ 100)	0.05	Year>2018 $\times \mathbb{1}$ (size $>$ 40)	0.01
	0.03		0.05		0.04
VA	0.01	Is Renewable$\times \mathbb{1}$ (size $>$ 500)	0.02	Queued in 2013-2015	0.12
	0.03		0.09		0.04
WV	-0.07	Is Renewable$\times \mathbb{1}$ (2013-2015)	0.14	Queued in 2016-2018	0.17
	0.05		0.10		0.07
Total capacity in-service	-0.00	Is Renewable$\times \mathbb{1}$ (2013-2015, size>40MW)	0.02	Queued after 2018	0.39
in 100km radius	0.00		0.16		0.09
Require more than 1 study	0.11	Is Renewable$\times \mathbb{1}$ (2016-2018)	0.07	Wait time>4 years	-0.37
	0.03		0.13		0.07
lnsize	0.00	Is Renewable$\times \mathbb{1}$ (2016-2018, size>40MW)	0.13	Const.	-0.08
	0.01		0.15		0.09
size>100MW	-0.07	Is Renewable$\times \mathbb{1}$ (year>2018)	0.22		
	0.04		0.14		
size>500MW	-0.11	Is Renewable$\times \mathbb{1}$ (year>2018, size>40MW)	0.14		
	0.05		0.14		

Table C.8: Full Model Estimates: Waiting Cost o

Const.	0.00	Study 1 at t β_{o1}	0.03
	0.00		0.01
Wait time>4years	-0.06	Study 1 at t, $\ln \text{cap}$ $\tilde{\beta}_{o1}$	-0.00
	0.01		0.00
Is Renewable$\times\mathbb{1}$ (2013-2015)	-0.00	Study 1 at $t-1$, β_{o2}	0.04
	0.00		0.01
Is Renewable$\times\mathbb{1}$ (2016-2018)	-0.00	Study 1 at $t-1$, $\ln \text{cap}$ $\tilde{\beta}_{o2}$	-0.00
	0.00		0.00
Is Renewable$\times\mathbb{1}$ (year>2018)	-0.00	Study 2 at t β_{o3}	-0.02
	0.00		0.01
Year 2013-2015	0.00	Study 2 at t, $\ln \text{cap}$ $\tilde{\beta}_{o3}$	-0.00
	0.00		0.00
Year 2016-2018	0.00	Study 2 at $t-1$, β_{o4}	0.11
	0.00		0.01
Year>2018	-0.00	Study 2 at $t-1$, $\ln \text{cap}$ $\tilde{\beta}_{o4}$	-0.01
	0.00		0.00