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AND CORPORATE PROFITS

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Power Flows: Transmission Lines, Allocative Efficiency, and Corporate Profits  
Catherine Hausman  
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**ABSTRACT**

Economists, energy experts, and policymakers have called for accelerating investment in the U.S. electricity transmission network. Additional transmission lines could better integrate markets, reducing the total cost of electricity generation. They could also allow for the better integration of renewable energy sources such as wind and solar, located in areas that traditionally did not have much generation capacity and that are far away from centers of demand. In this paper, I document the magnitude of static allocative inefficiencies induced by transmission congestion in two major U.S. electricity markets. I show that the allocative inefficiencies have risen over time, totaling more than \$2 billion in 2022. Moreover, I document an important political economy dimension not yet explored in the literature: the magnitudes of gains and losses from this market integration at some individual firms is surprisingly large: four firms would have experienced a collective \$1.6 billion drop in net revenues in 2022 had the market been integrated. I then tie some of these firms to reports of transmission hold-up in these markets. I argue that understanding firm-level gains and losses is just as important as understanding overall inefficiencies, particularly in an environment where incumbents may have the power to block new lines.

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# 1 Introduction

Market integration lowers aggregate production costs and brings gains from trade. This is especially true for electricity markets, where supply costs can be quite convex and where spatial integration can substitute for a lack of widespread storage. Moreover, grid integration – high-voltage transmission lines – is widely believed to be a key part of decarbonization strategy (Joskow, 2021; National Academies of Sciences, Engineering, and Medicine, 2021). Indeed, some scenarios have called for tripling the capacity of the U.S. grid by 2050 (Davis, Hausman and Rose, 2023).

The reason transmission may be particularly important in a transition towards decarbonization is that the grid of today is not spatially matched to the needs of a near-term decarbonized economy. Renewable resources like wind and solar are located in parts of the country that historically were not large sources of generation, and they are distant from most urban centers. New transmission lines have not kept up with these new sources of generation, and as a result renewable energy gets “curtailed” (dumped) even at times when more expensive fossil plants are running in other regions. Concurrently, wholesale electricity prices have been low in renewable-rich regions, even though prices remain high in other regions (Seel et al., 2021), weakening incentives for new renewable investment.

In this paper, I study two major wholesale electricity markets in the heart of the U.S.: the Southwest Power Pool (SPP) and the Midcontinent Independent System Operator (MISO). Combined, these markets cover a renewable-rich swath of the windy Midwest, as well as demand centers stretching from Minneapolis and Detroit to New Orleans. I construct supply curves under counterfactuals with and without transmission constraints, calculating the allocative inefficiencies caused by inadequate transmission infrastructure. I also construct counterfactuals where the alleviation of transmission constraints means that wind is no longer curtailed.

I find that in the recent past, transmission constraints were not particularly expensive, with static allocative inefficiencies averaging \$300 to \$400 million per year over the 2016-2020 period.<sup>1</sup> However the costs of transmission constraints have been rising, totaling more than \$2 billion in 2022. The increase over time has come from both rising natural gas prices through 2022 (which rotate the supply curve for wholesale electricity), and rising curtailments. Moreover, as I discuss below, there are additional costs on top of the \$2 billion: dynamic allocative inefficiencies, as well as reliability value.<sup>2</sup>

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<sup>1</sup>Dollar values throughout are reported in \$2022; I deflate using the CPI - all items less energy.

<sup>2</sup>There are three dimensions to dynamic allocative inefficiencies. Gonzales, Ito and Reguant (Forthcoming) shows that wind *entry* decisions are impacted by transmission constraints. Johnston, Yifei and Yang (2023) investigate how a separate kind of transmission planning problem – the delays new generators face

To further examine the causes of the estimated allocative inefficiencies, I next examine the observed behavior of individual power plants in these markets. I document that power plants tend to be dispatched in response to shocks within their own market (i.e., MISO plants in response to MISO demand). More striking, I find that plants tend to be dispatched in response to demand shocks in their own *subregion* of their market. I find an especially striking divide between the Southern part of MISO (the Gulf Coast) and the Northern and Central parts (the Great Lakes).

It is of course possible that the \$2 billion in allocative inefficiencies I document for 2022 are socially optimal, if the cost of building new transmission lines is very high.<sup>3</sup> However, many grid observers have argued that the transmission planning, siting, and permitting processes in the U.S. do not lead to socially optimal investments, in particular for long-distance lines crossing regions. Davis, Hausman and Rose (2023) point to myriad roadblocks, ranging from NIMBY-ism concerns to bureaucratic procedures for cost allocation.

To examine one potential source of transmission planning failures, I turn to empirical estimation of the potential firm-level gains and losses from market integration. While gains from trade in the *aggregate* are to be expected, it is also to be expected that some agents will lose – in particular, incumbent generators in high-cost regions.<sup>4</sup> There is of course nothing problematic with this for overall social welfare, but understanding which power plants, which regions, and which firms stand to lose can point towards political economy barriers.

I next show that the rise in wind energy in recent years has decreased net revenues for fossil incumbents – but crucially, by less than it would have had the market been fully integrated. That is, fossil incumbents have been partially protected from new competitors by a lack of transmission. Second, I show that the overall effect on incumbents masks important heterogeneity. There is a pronounced regional pattern to which incumbents would lose the most from integration, with firms in South MISO – an area known for inadequate connections to nearby regions – standing to lose the most.

Finally, I show that the potential losses to net revenues are very large for some firms. The four firms with the most to lose would have earned a combined \$1.6 billion less in net revenues in 2022. The majority of firms in my sample are rate-of-return regulated, and below

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in obtaining interconnections – impacts renewable development. And finally, transmission constraints may impact retirement decisions of existing generators.

<sup>3</sup>I do not perform a cost/benefit analysis of new transmission in this paper, as I do not observe the full social costs of new transmission lines, nor the scale of new investment that would be needed to remove all congestion. Engineering papers evaluating the optimal level of transmission under various assumptions include Brown and Botterud (2021); Princeton (2021); Williams et al. (2021); Bloom et al. (2022).

<sup>4</sup>As I discuss below, other losers include consumers in some regions, who would see rising prices. Winners include generators currently experiencing low prices, who would be able to export their power to locations that are currently load pockets. Consumers in load pockets would also win. And finally, new renewables entrants could win as prices rise in windy parts of, e.g., the Great Plains.

I discuss how net revenues are related to profits for these firms.

Not surprisingly, the two firms (in fact, two subsidiaries of the same firm) with the most to lose are in the Southern MISO region. Moreover, these two firms have been accused for decades of blocking new transmission lines. The tactics they have been accused of range from preventing competitors from accessing the firm’s transmission network, to slow-walking the market-wide transmission planning process, to hiring a consultant to pose as a concerned customer in public hearings.

A notable gap in the empirical literature on transmission networks is documentation of the magnitude of gains and losses to individual incumbent firms. Numerous papers cite this problem qualitatively (Hirst and Kirby, 2001; Hogan, 2018; Wolak, 2020; Cicala, 2021; Joskow, 2021; Davis, Hausman and Rose, 2023), but empirical estimates are rarely reported.<sup>5</sup> This is of particular importance given claims in the literature that “losers” may be holding up the transmission planning process. If the allocative inefficiencies that are becoming widely documented are a result of the planning process in the U.S., then understanding incentives for firms to block market integration is of policy relevance.

The paper most directly related to my analysis is Gonzales, Ito and Reguant (Forthcoming), which conducts a thorough examination of the role of transmission expansion in both the short-run dispatch and long-run investment decisions of the Chilean electricity market. Of most relevance for what I do, that paper shows how allocative inefficiencies arise as a result of transmission bottlenecks, and how these are exacerbated by renewables curtailments (in this case, solar). Another paper considering the dynamic relationship between renewables and the transmission grid is Johnston, Yifei and Yang (2023), which looks at interconnections – the transmission lines specifically needed for new renewables hook-ups – in the PJM market. My paper complements their work by focusing on the across-region transmission constraints impacting existing generators.

Other related papers on the interaction of renewable generation and transmission network expansion include Jorgenson, Mai and Brinkman (2017); Qiu (2020); Brown and Botterud (2021); Fell, Kaffine and Novan (2021); Bloom et al. (2022); Doshi (2022); LaRiviere and Lyu (2022); Yang (2022); Kemp et al. (2023), and Lamp and Samano (2023). These papers study a variety of markets (Texas, Germany, and more) using a variety of modeling techniques. Taken as a whole, these papers show how transmission and renewable generation can be complements. This relates to evidence on the spatial misallocation of renewables investments in the U.S. to date (Callaway, Fowlie and McCormick, 2018; Sexton et al., 2021).

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<sup>5</sup>There are papers that estimate the impacts of transmission constraints (or their alleviation) on the revenues of wind and solar sources – particularly *new* wind and solar – (Gonzales, Ito and Reguant, Forthcoming; Johnston, Yifei and Yang, 2023; Kemp et al., 2023), but they generally do not investigate the impacts on incumbent fossil generators.

There is also a broader literature on allocative inefficiencies arising from transmission constraints in electricity markets even aside from their interaction with renewable generation. Some of these papers emphasize how opportunities to exercise market power are increased in the presence of transmission constraints (Wolak, 2015; Davis and Hausman, 2016; Ryan, 2021). The transmission network also has an important role in enhancing grid reliability (Borensten, Bushnell and Mansur, 2023). And finally, there is a broader literature on the regional integration of electricity markets, relating to market design rather than to physical transmission constraints (Mansur and White, 2012; Cicala, 2022).

The paper proceeds as follows. In Section 2, I provide brief contextual background. Section 3 summarizes the data sources I use. Section 4 summarizes the methods and results on allocative inefficiencies. Section 5 explores net revenue impacts for incumbents firms. Section 6 shows various robustness checks, and Section 7 concludes.

## 2 Background

In this Section, I provide brief contextual background. I study two U.S. electricity markets, the Southwest Power Pool (SPP) and the Midcontinent Independent System Operator (MISO). Each is a non-profit entity responsible for operating the electricity grid within their footprints: matching supply and demand offers, as well as ensuring grid reliability.

SPP’s members are in fifteen states, roughly covering the Great Plains region from Montana to Texas.<sup>6</sup> MISO also covers fifteen states (roughly, from North Dakota to Michigan and south to Louisiana) and one Canadian province.<sup>7</sup> Some states are split between both SPP and MISO, but one can broadly think of SPP as covering the Great Plains and MISO as being more to the east (the Great Lakes and the Gulf Coast).

Both SPP and MISO are part of the Eastern Interconnection. The U.S. electricity grid is physically divided into three such interconnections: one in the western half of the country, one in the eastern half, and one covering most of Texas. There is almost no transmission between the three grids, a legacy of the way the grid originally developed in the U.S.

The generation mix of both MISO and SPP includes a mix of fossil power plants (coal and natural gas), nuclear, and a growing supply of wind (particularly in SPP). Both regions have small quantities of hydro, solar, and other units (e.g. thermal plants fueled by solid

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<sup>6</sup>SPP’s members are in Arkansas, Colorado, Iowa, Kansas, Louisiana, Minnesota, Missouri, Montana, Nebraska, New Mexico, North Dakota, Oklahoma, South Dakota, Texas and Wyoming – some (such as Colorado and Wyoming) are only partly covered by SPP.

<sup>7</sup>The states covered are Arkansas, Illinois, Indiana, Iowa, Kentucky, Louisiana, Michigan, Minnesota, Mississippi, Missouri, Montana, North Dakota, South Dakota, Texas, and Wisconsin – some (such as Montana and Texas) are only partly covered by MISO.

waste). Summary statistics are provided below.

Both SPP and MISO have independent market monitors, who evaluate the functioning of each market, including both reliability metrics and whether generators appear to be exercising market power. Annual reports from both market monitors covering my sample period indicate very competitive generation markets.

### 3 Data

I build a detailed panel dataset on these two major U.S. electricity markets (SPP and MISO), incorporating data from several government agencies as well as both market operators. Here I provide a brief overview; descriptive statistics are in the Appendix.

From the U.S. Environmental Protection Agency’s CEMS dataset, I observe hourly generation<sup>8</sup> and hourly fuel use at individual thermal generating units; a typical power plant has between one and eight generating units.<sup>9</sup>

Also from CEMS, I observe each unit’s fuel type (coal, natural gas, and oil), technology (boiler, combined cycle, or combustion turbine), and location (latitude and longitude). The majority (74 percent) of units in my sample use natural gas, 21 percent use coal, and only five percent use oil. From the Energy Information Administration’s EIA-860 survey, I observe additional characteristics of each plant: its location in MISO versus SPP, the name of its owner, and whether its owner is an investor-owned utility or a merchant generator. Two thirds of the units I observe are in MISO, which has a larger footprint than SPP. The majority of units in my sample are operated by investor-owned utilities.

From the CEMS hourly generation and fuel use, I calculate each unit’s heat rate, a measure of how efficiently it converts fuel into electricity (and a primary component of marginal cost). I calculate each unit’s capacity as the 99th percentile of observed generation. Generating units are taken offline frequently for maintenance, so I use monthly outage rates from a market monitoring report (Potomac Economics, 2022).

The two market operators also release detailed data. From each, I observe ISO-wide hourly generation by fuel type – this is important for understanding the behavior of nuclear

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<sup>8</sup>The reported generation in the CEMS dataset is “gross” rather than “net” – the difference is generation used for in-house operations, and therefore not sold on the wholesale market. To convert from gross to net generation, I follow the literature (Cicala, 2022) in matching gross generation from CEMS to net generation from the Department of Energy’s Energy Information Administration’s EIA-923 dataset (available at the annual level), then constructing a plant-specific conversion factor.

<sup>9</sup>The hourly EPA data are limited to generating units with a capacity of at least 25 MW; smaller units are observable only at the annual level, from a separate data source (the Energy Information Administration’s EIA-923 survey, or the EPA’s eGrid dataset). However, the average capacity of a coal or natural gas fired unit in the U.S. in 2021 was 120 MW, so these unobserved units are quite small – they make up only around 1 percent of total coal and natural generation, according to the EPA’s eGrid 2021 dataset.

and renewable generation, as those fuel types are not represented in the CEMS data.<sup>10</sup> I also assemble wind curtailment data from the ISOs.<sup>11</sup> Each ISO also reports total quantity demanded at the hourly level (called “load” in electricity markets) for various regions.<sup>12</sup> From EIA’s 930 dataset, I observe load in the Eastern Interconnection as a whole.

Fuel prices are published by the EIA; I use both daily upstream prices (the Henry Hub natural gas price and the West Texas Intermediate (WTI) oil price) and monthly downstream prices (the average fuel price paid by power plants for coal, natural gas, and oil). Finally, daily temperatures are published by the National Oceanic and Atmospheric Administration (NOAA).

## 4 Allocative Inefficiencies

### 4.1 Constructing Marginal Cost Curves

To construct market-wide marginal cost curves, I first construct the marginal cost  $mc$  of each thermal generating unit  $i$  in each hour  $t$  as follows:

$$mc_{i,t} = fp_t \cdot hr_i + om_i + ec_{i,t} \quad (1)$$

where  $fp$  is the fuel price in each hour (in dollars per mmBtu),  $hr$  is the heat rate of each unit (in mmBtu per MWh),  $om$  is the unit’s variable operating and maintenance costs (in dollars per MWh), and  $ec$  is the environmental compliance cost (in dollars per MWh).

Recall that the EIA publishes both monthly data on average prices paid for fuel by power plants and daily upstream fuel prices (Henry Hub for natural gas and WTI for oil). It is important to capture both this daily variation for natural gas and oil as well as the markup, so I construct fuel prices as the upstream price (varying daily) plus a time-invariant average markup (the sample-wide difference between the upstream and downstream prices reported by EIA). Coal prices have very little variation across days within a month, so I simply use EIA’s monthly data on average price paid by power plants. I assume technology-specific  $om$  values from Energy Information Administration (2019) where possible and otherwise from

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<sup>10</sup>MISO but not SPP also releases hourly generation by fuel type at a broad regional level (North, Central, South) – which I leverage later when examining counterfactual revenues.

<sup>11</sup>From SPP, I observe hourly wind quantity curtailed. MISO does not make hourly curtailment data available, but I assemble daily curtailment data, separated into peak and off-peak periods, for December 2019 through December 2022 from the slide decks published for MISO’s monthly Informational Forum web presentations.

<sup>12</sup>MISO reports load across three broad regions (North, Central, and South). SPP reports more disaggregated regions – around a dozen – which I aggregate to three broad regions to parallel the regional definitions I have for MISO.



Energy Information Administration (2022).

An additional, albeit quite minor, marginal cost for most units in my sample is the cost paid to purchase permits to cover pollution emissions. Units in these states are covered by EPA cap and trade programs for sulfur dioxide and nitrogen oxides emissions. I observe hourly emissions from the EPA CEMS dataset and annual permit prices from the EPA’s Power Sector Programs Progress Reports, from which I calculate total environmental compliance costs.<sup>13</sup> These costs have at some points in U.S. history been very high, but for my sample this increases marginal cost by less than one percent on average.

Summing across the three components of marginal cost, I obtain marginal costs, in dollars per MWh, that are generally in line with the literature. A small number of values are implausible (e.g. because I estimate a very high heat rate at some units), so I winsorize marginal costs at the 1st and 99th percentiles.

My primary sample focuses on the coal, natural gas, and oil power plants for which marginal costs are well-known. My primary sample drops a small number of thermal units with fuel types such as wood and municipal solid waste; these make up less than one percent of CEMS generation. As my primary analysis constructs counterfactuals regarding changing the dispatch of thermal units, this is akin to assuming that the behavior of wood and waste units does not change in my counterfactuals. Similarly, I drop commercial and industrial and cogeneration units (e.g., generating units located at chemical plants, hospitals, and universities) – again, marginal costs at these units are not clear, and dropping them is simply assuming that they would not respond to changes in market incentives.

Marginal costs for renewables and nuclear generation do not depend on heat rates and permit prices. Following the literature, I assume that renewables (wind, solar, and hydro) have zero marginal cost.<sup>14</sup> Capacity for these types varies across hours, depending on weather (e.g. how windy it was that hour). I construct capacity as observed generation for each fuel type, plus the quantity curtailed. For nuclear units, I assume a marginal cost based on the average operating expenses for nuclear units reported in Energy Information Administration (2023).<sup>15</sup> I also assume that nuclear units will not respond to short-term fluctuations in

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<sup>13</sup>Specifically, I calculate a time-invariant emissions rate for each unit, in tons of pollutant per MWh of generation; I multiply this by the permit cost, which is in dollars per ton of pollutant.

<sup>14</sup>Most papers on electricity markets in the West must make more complex assumptions about hydroelectric behavior, as dams allow operators to store some of their capacity for when prices are high. Modeling this correctly is important in the West, where hydro is a substantial source of electricity – this is much less true in MISO and SPP, where hydro is relatively small. Hydro provided only two percent of generation across MISO and SPP in 2021, but it provided more than 30 percent of generation across the West Coast (California, Oregon, and Washington).

<sup>15</sup>Table 8.4 of Energy Information Administration (2023) reports average fuel costs of around \$6.80/MWh for my sample period. Operations and maintenance (O&M) costs average \$16.80/MWh; I assume that half of these are fixed O&M and half are variable O&M, i.e. half are marginal to generation. This gives a marginal

wholesale prices because of their operational constraints (Davis and Hausman, 2016), and thus I fix their generation at what I empirically observe in each hour.

The other variable needed at each thermal generating unit is its maximum capacity. As described in the data section, I use empirically observed capacities. However, I must also apply outages, as units go offline for both planned and unplanned maintenance. In my primary specification, I stochastically apply outages across all unit/hour combinations, similar to what is done in Borenstein, Bushnell and Wolak (2002).<sup>16</sup>

With hourly marginal costs and annual capacities constructed as described above, I can construct market-wide marginal cost curves.<sup>17</sup> For my first counterfactual, I use a least-cost dispatch framework: I rank the units by their marginal cost, then dispatch units until demand is met, where demand is defined as the total quantity generated in the real world in hour  $t$  across all generators. That is, in each hour  $t$ , I choose quantities  $g$  generated at each unit  $i$  to minimize the total cost of production, in order to meet market-wide demand, subject to a capacity ( $C$ ) constraint at each unit:

$$\min_{g_{i,t}} \left( \sum_{i \in (1,2,\dots,I)} mc_{i,t} g_{i,t} \right) \quad s.t. \quad \sum_{i \in (1,2,\dots,I)} g_{i,t} = demand_t; \\ g_{i,t} \leq C_{i,t} \quad \forall i; \tag{2}$$

This approach is widely used in the literature in both economics and engineering (Borenstein, Bushnell and Wolak, 2002; Deetjen and Azevedo, 2019; Mills et al., 2021; Cicala, 2022).<sup>18</sup> A limitation of this approach is that it ignores transmission constraints and various technical constraints of generating units themselves (ramping costs and other dynamic considerations, and minimum dispatch constraints). Below, I augment with additional counterfactuals to incorporate additional constraints.

An example marginal cost curve is shown with a grey line in Figure 1. I choose a sample hour that is “typical” in terms of total quantity demanded, fuel prices, and wind cost estimate of \$15.15/MWh, comparable to the California-specific estimate used in Davis and Hausman (2016).

<sup>16</sup>Unlike Borenstein, Bushnell and Wolak (2002), I do not Monte Carlo over these stochastic outages; given the large number of unit/hour combinations (more than 53 million) in my sample – each of which receives an independent draw – it is unlikely that the particular random draw I use will affect my results.

<sup>17</sup>Some empirical approaches would leverage equilibrium price data, rather than construct supply curves. I do not do so for two reasons. First, to calculate allocative inefficiencies, I need to integrate under the entire supply curve in each hour, whereas hourly prices give me a single point on the supply curve. Second, and relatedly, electricity cost curves are highly nonlinear at any point in time, and they vary substantially across time with fuel prices and wind availability; as such, one cannot simply assume an elasticity to back out the cost curve from a given observed equilibrium price and quantity.

<sup>18</sup>Note the terminology used varies; for instance, Mills et al. (2021) refers to this approach as a “fundamental supply curve model.”

quantity curtailed for 2022; additional sample hours representing different market conditions are shown in the Appendix. For this hour, 34,000 MWh of generation are provided by zero-cost renewables, an additional 13,000 MWh by nuclear, and then the remaining 42,000 MWh are provided by a mix of thermal generating units, primarily coal boilers. Across all hours in my sample, thermal generation is provided by a mix of fuel and technology types, where marginal cost varies across units because of varying heat rates and fuel prices.

## 4.2 Modeling Transmission Constraints

For the second counterfactual, I assume that the system is constrained in two ways. First, I incorporate regional transmission constraints. I model transmission constraints in a reduced form way as follows. I assign each generating unit to a North American Electric Reliability Corporation (NERC) subregion as reported in the EPA eGRID dataset (see Appendix for map).<sup>19</sup> NERC is a non-profit organization that oversees electric grid reliability in the U.S., Canada, and part of Mexico, and it monitors reliability across approximately two dozen subregions. I infer transmission constraints across subregions at the hourly level by calculating the total quantity supplied by thermal generating units in each hour in each subregion using the CEMS generation data. As I dispatch units using the least-cost dispatch algorithm described above, I constrain total generation in each subregion in each hour to what I empirically observe. That is, I force each subregion to generate no more than what was actually generated in the real world.<sup>20</sup>

The optimization problem is thus:

$$\min_{g_{i,t}} \left( \sum_{i \in (1,2,\dots,I)} mc_{i,t} g_{i,t} \right) \quad s.t. \quad \sum_{i \in (1,2,\dots,I_r)} g_{i,t} = obs\_gen_{r,t} \quad \forall r \in R;$$

$$g_{i,t} \leq C_{i,t} \quad \forall i; \tag{3}$$

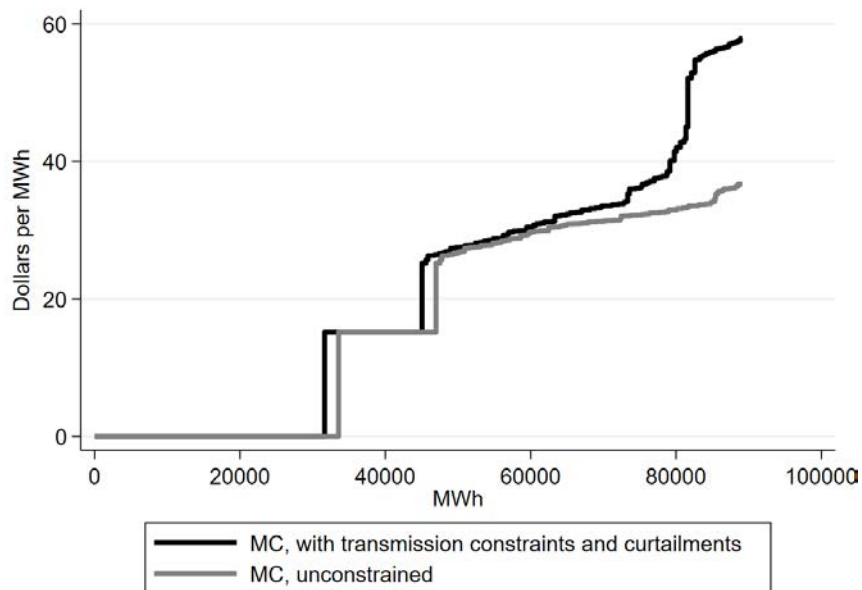
where the total generation constraint must be met *within* each region  $r$ , and where the total generation constraint is defined as the region-wide observed generation in the real world in hour  $t$ :  $obs\_gen = \sum_{i \in (1,2,\dots,I_r)} g_{i,t}^{observed}$ . Thus the *flows* of generation across regions cannot

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<sup>19</sup>I use the mapping from power plants to NERC subregions available from the Environmental Protection Agency’s eGRID database. This yields a very small number of units in ERCT, SRSO, and SRTV, three NERC subregions that primarily do not lie in MISO or SPP (one plant in ERCT, two in SRSO, and four in SRTV). I assign these plants to SPSO, SRMV, and RFCW, respectively, so as to not overstate how binding transmission constraints might be to the ERCT, SRSO, and SRTV regions.

<sup>20</sup>In a small number of hours, my model predicts that too little capacity is available in some regions. This is because of the outage patterns I impose. In these hours, I force all units to operate slightly above their capacity. This changes generation by more than 10 MWh for fewer than 0.1 percent of observations.

Figure 1: Example Marginal Cost Curves, With and Without Transmission Constraints and Wind Curtailments



Note: This figure shows two constructed marginal cost curves for a representative hour in 2022, for the entire SPP and MISO market, up to the quantity demanded in that hour. The grey line shows the marginal cost curve for least-cost dispatch, with no restrictions on electricity flows across space, and with no curtailment on the dispatch of wind. In contrast, the black line constrains quantities generated within a NERC subregion to the quantity observed in the actual data (to approximate transmission constraints), and curtails wind generation at the level observed in the actual data. Zero marginal cost resources are largely wind, but also include hydro and solar generation. Nuclear generation is assumed to have a marginal cost of \$15/MWh. The remaining units are powered by coal and natural gas, with differences in marginal cost reflecting differences in heat rates and fuel type. The date and hour displayed are chosen because they have fuel costs, quantity demanded, and quantity curtailed close to the sample average for 2022. Additional date-hour combinations (with alternative fuel costs, quantity demanded, and quantity curtailed) are shown in the Appendix.

be greater in my model than whatever they were in the real market in hour  $t$ , where the latter was a function of the (unobserved) physical grid, including individual transmission line capacity constraints and time-varying weather shocks that impact transmission line performance. In two robustness checks, I maintain this methodology but vary the geographical boundaries of the regions.

This counterfactual also assumes that wind generation is curtailed because of transmission constraints, following what I see in the real world. Whereas the first counterfactual constructs wind capacity as equal to observed generation in each hour plus observed quantity curtailed in each hour, this second counterfactual constructs wind capacity as equal to only observed generation in each hour.

Ideally, one would model the actual topology of transmission constraints, but that is not feasible here for several reasons. Accurate modeling of the transmission network would require knowing the physical topology of the grid, including not only line locations but also line ratings (the capacity of each line); detailed information on this topology is not publicly available. Furthermore, modeling the flow of electrons across this network is complicated. One should not picture something like a pipeline network for natural gas or water, in which one would simply need to observe quantities flowing in and out of the pipelines. Instead, electron flow across a network is governed by complex laws of physics (Joskow, 2012; Borenstein, Bushnell and Mansur, 2023). Moreover, congestion is constantly changing – both in where it impacts the grid and in how binding it is – as demand, generation, and weather change; and the inputs to this complex process are not all observable.

Many existing papers on transmission study simple two-node problems; California and Chile each predominantly have a North-South transmission constraint, and pre-CREZ Texas had a West-East constraint.<sup>21</sup> In contrast, my setting features a complex set of interregional constraints. As such, my reduced form model can provide a reasonable approximation that uses publicly available data, that can be calculated for multiple regions in every hour using observable data, and that is computationally not too burdensome.

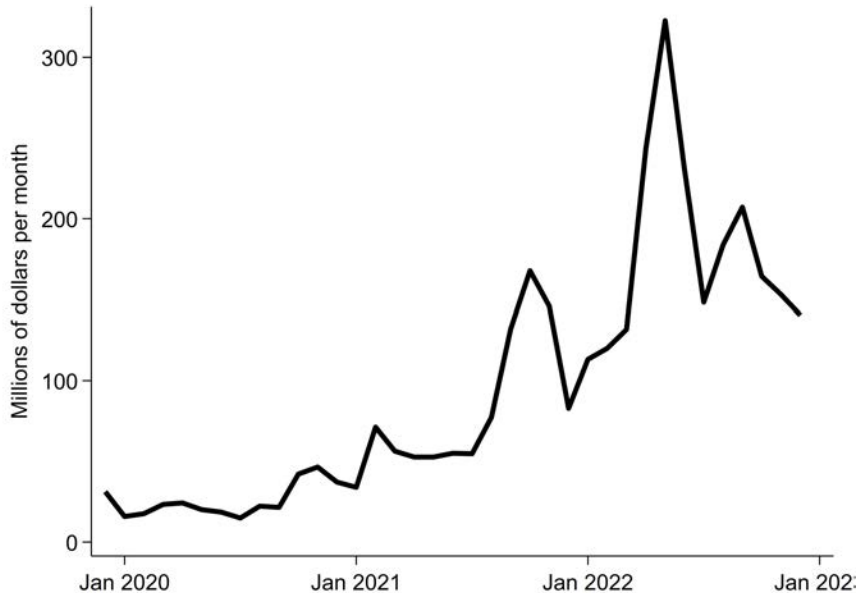
The market-wide marginal cost curve for this second counterfactual is shown with the black line in Figure 1. Zero-cost generation shifts inward, by the quantity curtailed. Nuclear units are unaffected, by construction.<sup>22</sup> Also, some higher-cost thermal units must be dispatched because of the regional transmission constraints.

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<sup>21</sup>The Competitive Renewable Energy Zone (CREZ) project brought transmission expansion that better integrated windy west Texas with demand centers in the eastern part of the state (Fell, Kaffine and Novan, 2021).

<sup>22</sup>As described above, it is technologically difficult and expensive to ramp nuclear units up and down; as a result, nuclear units are very rarely curtailed. They are occasionally forced to limit their generation because of safety concerns, which I do not model as part of this counterfactual.

Figure 2: Additional Generation Costs From Transmission Constraints and Wind Curtailments



Note: This figure shows the monthly generation costs in MISO and SPP that arise from transmission constraints and renewables curtailments. Transmission constraints are modeled at the NERC subregion level and so do not include within-subregion transmission constraints. Costs have risen over time from a combination of increasing natural gas prices and increasing curtailments. Robustness checks are shown in the Appendix. Additional time series, holding various factors constant, are also shown in the Appendix.

### 4.3 Calculating Allocative Inefficiencies

The wedge between the black and gray lines in Figure 1 represents the additional costs required to generate electricity that are induced by regional transmission constraints and the need to curtail wind. By calculating the area between the two curves in each hour, I can construct a time series of the allocative inefficiencies induced by transmission constraints and wind curtailments. That is, for each hour  $t$  I calculate  $\sum_i mc_{i,t}g_{i,t}^\dagger - \sum_i mc_{i,t}g_{i,t}^*$ , where  $g_{i,t}^\dagger$  are equilibrium quantities from equation (3), and  $g_{i,t}^*$  are equilibrium quantities from equation (2).

Figure 2 shows this time series, aggregated to the monthly level. I focus on 2020 through 2022, the period for which wind curtailments data are available from MISO; a time series with inferred wind curtailments for 2016-2020 is shown in the Appendix.

Figure 2 shows that transmission and curtailment-related allocative inefficiencies have been rising over time for the MISO and SPP markets. This is a combination of increasing curtailments and increasing natural gas prices, as detailed below. By 2022, the average

Table 1: Annual Allocative Inefficiencies

Annual cost, billion dollars	2016-2020	2021	2022
Total	0.32 to 0.43	0.98	2.16
Across-ISO constraints	0.03	0.10	0.21
Within-ISO constraints	0.25	0.57	1.31
Curtailements	0.03 to 0.14	0.31	0.64
Within-SPP constraints	0.08	0.12	0.19
Within-MISO constraints	0.18	0.45	1.12

Note: This table shows the average annual generation costs in MISO and SPP stemming from transmission constraints and renewables curtailments. Matching Figure 2, the table shows the increase after 2021 in these costs. The next three rows decompose the 2022 cost into three factors: renewables curtailments, transmission constraints between MISO and SPP, and transmission constraints across NERC sub-regions within MISO and SPP. The bottom two rows separate within-ISO constraints into those within MISO and those within SPP.

monthly allocative inefficiencies total \$180 million, translating to more than \$2 billion for 2022. Table 1 shows an annual summary of the allocative inefficiency.

For the sample as a whole, annual allocative inefficiencies total \$0.7 to \$0.8 billion dollars (the range comes from what one assumes about MISO wind curtailments for the 2016-2019 period). However, this average masks a large difference between the 2016-2020 period – with an annual average of \$0.3 to \$0.4 billion dollars – and the 2021-2022 period – with annual inefficiencies of \$0.98 billion in 2021 and \$2.16 billion in 2022.

This stark difference in 2022 costs is primarily the result of increasing curtailments and increasing natural gas costs, as I show in two different ways. First, I regress the hourly inefficiency, i.e. additional cost  $c$ , on total demand  $d$  across the two ISOs, potential wind generation  $w$ , and fuel prices (natural gas  $n$  and oil  $o$ ), with a log/log specification:

$$\ln c_t = \beta_1 \ln d_t + \beta_2 \ln w_t + \beta_3 \ln n_t + \beta_4 \ln o_t + X_t \Theta + \varepsilon_t \quad (4)$$

Following the literature, I include controls  $X$  for weather (heating and cooling degree days), and various time effects (month of sample, day of week, hour of day). Note that coal prices are measured at the monthly level and are thus subsumed by the month of sample effects. Table 2 shows the results; alternative specifications are shown in the Appendix.

Not surprisingly, the wedge is larger when demand is higher; the wedge is also larger when natural gas prices are higher.<sup>23</sup> Perhaps most of interest, the wedge increases with potential

<sup>23</sup>Oil generation is very small, so oil prices do not materially impact the wedge. Coal prices are subsumed by month of sample effects. In any case, coal prices are very stable over this time period and not likely to contribute to changes in the wedge over the sample.

Table 2: Allocative Inefficiencies Increase as Wind Curtailments Increase

	(1)	(2)
Demand	2.13*** (0.11)	2.13*** (0.10)
Natural gas price	1.26*** (0.10)	1.28*** (0.09)
Oil price	0.02 (0.16)	0.09 (0.10)
Wind generation + curtailments	0.17*** (0.02)	
Wind generation		-0.16*** (0.01)
Wind curtailments		0.27*** (0.01)
Observations	61,242	61,008
R <sup>2</sup>	0.73	0.80

Note: The unit of observation is an hour. The dependent variable is the log of the hourly allocative inefficiency induced by transmission congestion. The independent variables of interest are total demand, total wind potential (generation plus curtailments), and fuel prices. Additional controls are heating and cooling degree days and time effects (month of sample, day of week, hour of day). Standard errors are clustered by sample month and by sample week.

wind generation – as wind capacity has entered the market, it has led to an increase in allocative inefficiencies induced by transmission constraints. Interpretation of this coefficient is important: wind generation of course lowers the marginal cost of producing electricity (see Figure 1), but it lowers it by less than it would if the grid were fully integrated, so the allocative inefficiencies are increased. The implication is not that wind is not good for lowering costs, but rather that transmission is a complement to wind in this market.

To expand on this point, Column 2 of Table 2 breaks total wind out into two variables: generation that actually “made it to market,” and wind that was curtailed. This regression should be interpreted with some caution, as curtailments are endogenous to other system conditions. Nonetheless, to the extent they are induced by physical constraints on the system, they can be thought of as quasi-exogenous. The positive coefficient on wind comes entirely from curtailments – if these could be eliminated, wind would not contribute to allocative inefficiencies. Indeed, we see a negative coefficient on wind generation that did make it to market.

As another way to decompose the source of the increase in allocative inefficiencies over time, the Appendix shows the time series of the inefficiency holding various natural gas prices and/or curtailments constant. It shows that the increase in allocative inefficiency in 2022



is a result of both rising natural gas prices and rising curtailments, with more of the effect coming from natural gas price changes.

The increase over time points to important policy implications. First, it is clear why some policymakers and grid observers have been increasingly calling for new transmission infrastructure in recent years. The transmission network until recently basically did what it needed to – connecting thermal power plants to load in population centers. But in a world with increasing quantities of renewable generation, the existing network doesn’t match the spatial distribution of generation.

Second, low natural gas prices in recent decades had flattened the market-wide marginal cost curve for electricity. But with natural gas prices surging up in 2022, the marginal cost curve rotated, and dispatching the “wrong” unit – because of something like a regional transmission constraint – became much more expensive. My sample does not include 2023 (because of lags in data availability), but natural gas prices fell in 2023, and this is likely to pull allocative inefficiencies back down.

Returning to Table 1, I show various decompositions of the inefficiencies within a given time period. Rows 2 and 3 show that the largest source of the 2022 inefficiencies was within-ISO constraints (\$1.31 billion), whereas across-ISO constraints totaled only \$0.21 billion. The second largest source of inefficiencies was curtailments (\$0.64 billion, row 4). With wind facing a marginal cost of essentially zero, curtailing it and having to dispatch a fossil unit can significantly raise the costs of dispatch.

Moreover, the within-ISO constraints are largely coming from MISO rather than SPP (rows 5 and 6). This is in part simply due to the fact that MISO is larger, with more than double the hourly generation of SPP. However, it is also notable how much more within-MISO constraints have risen over time, relative to SPP; this is in part due to MISO’s larger quantity of natural gas generation (nearly triple that of SPP’s), combined with rising natural gas prices nationwide. I next turn to descriptive evidence of the sources of these transmission constraints.

## 4.4 Sources of Transmission Constraints

Section 4.3 shows that total generation costs can increase substantially if generation is regionally constrained. Specifically, in 2022, across-ISO and within-ISO regional constraints together added \$1.52 billion in generation costs for fossil units. Of this, the single largest source is within-MISO constraints (\$1.12 billion). To better understand these constraints, I next turn to evidence on observed generator dispatch.

Specifically, I use the CEMS data on hourly generation for each fossil generating unit in

MISO and SPP, and I run “horse race” regressions on the observed load in different regions. These regressions are designed to answer the question: to which load (demand) is generator dispatch most likely to respond? If the electrical grid were physically unconstrained, generators would be expected to respond equally to a demand shock in any location. If we observe that generators are more often dispatched in response to a demand shock in their own region, that suggests that the electrical grid is constrained in some way.<sup>24</sup>

I primarily rely on one identifying assumption: I must assume that demand shocks are exogenous. This assumption is made in most papers on electricity economics that use hourly generation – the majority of consumers do not face real-time prices, and so are not incentivized to respond to hourly shocks to supply.

I run a separate regression for each power plant, as follows:

$$g_{i,t} = \beta_1 d_{SPP,t} + \beta_2 d_{MISO,t} + \beta_3 d_{EI,t} + X_t \Theta + \varepsilon_{i,t} \quad (5)$$

where generation  $g$  at power plant  $i$  in hour  $t$  is a function of demand  $d$  in hour  $t$  in SPP, MISO, and the Eastern Interconnection. The U.S. electricity grid is divided into three interconnections, with very limited (nearly zero) flows across interconnections. MISO and SPP are both located in the Eastern Interconnection, so I control for demand in the rest of that interconnection (after subtracting MISO and SPP demand).

Under the assumption that demand is exogenous, additional control variables may not be needed for estimating equation (5). Nonetheless, I follow the literature in including controls  $X$  for fuel prices (natural gas, coal, and oil), weather (ambient temperature), a time trend, month-of-year effects, day-of-week effects, and hour-of-day effects. These controls may be useful for accounting for things like maintenance outages, planned for specific months of the year, which are correlated with demand. Additionally, the controls may help with precision. In the Appendix, I show results without controls.

I estimate equation 5 separately for each of the roughly 400 fossil plants in my CEMS sample,<sup>25</sup> with each regression using hourly data covering the 2016-2022 period.<sup>26</sup> I then

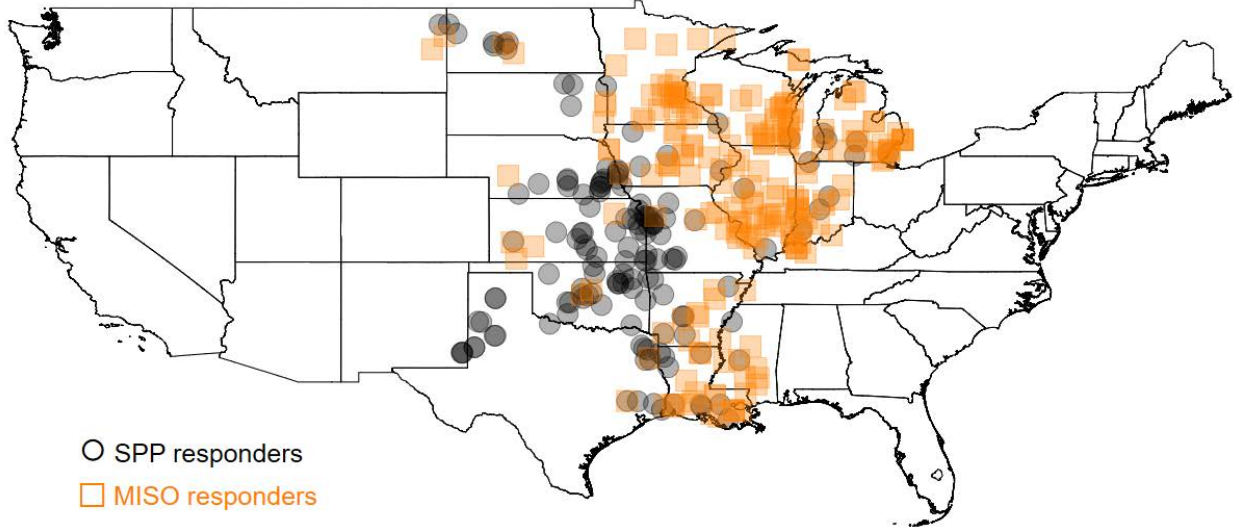
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<sup>24</sup>One could imagine instead regressing generation at each power plant on *prices* across regions; but this is not identified because of reverse causality. When plants are able to generate, prices will be lower, but what one wants to estimate is whether, when prices are higher, generators respond by increasing production. One could estimate this with some shifter of prices – for instance, hourly demand in each region. Essentially, I am estimating the reduced form version of such a 2SLS specification.

<sup>25</sup>For statistical power, I collapse to the plant level, rather than the unit level. Also, I drop a small number of plants that generate very infrequently; specifically, I keep only units with at least 336 non-zero generation hours, equivalent to two weeks over my seven-year sample.

<sup>26</sup>The primary sample for equation 5 drops a two week period in February 2021, when Winter Storm Uri disrupted energy markets in Oklahoma and Texas. During that period, natural gas prices spiked from around \$4/mmBtu to more than \$25/mmBtu (leading to outliers in my control variables), and some generators were forced to shut down because of weather. In the Appendix, I show results that include this period.

Figure 3: Power Plants Are Dispatched For Own-ISO Load



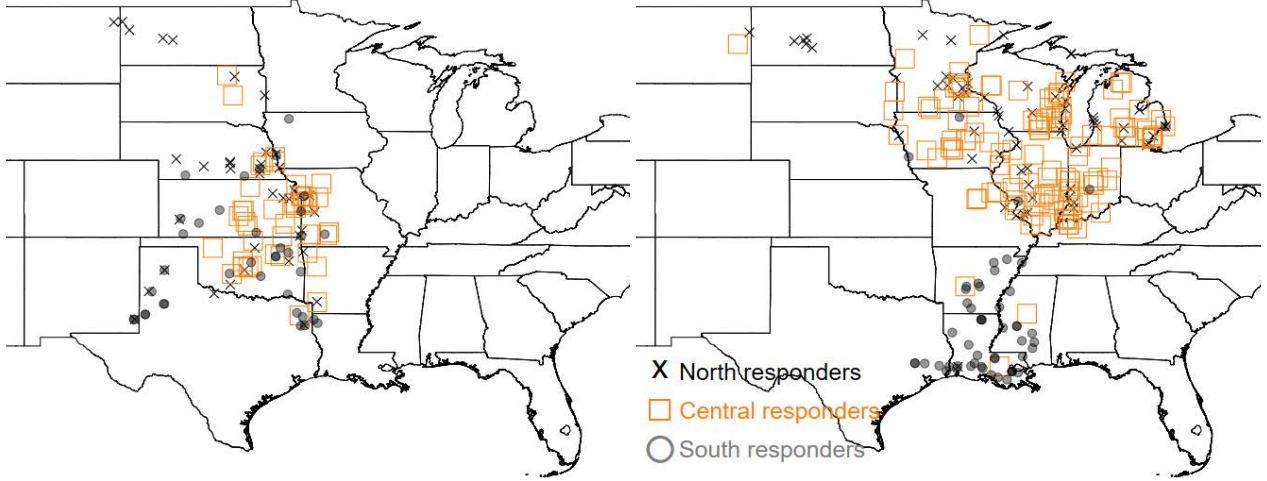
Note: This figure shows whether power plants are dispatched at higher levels of generation in response to SPP load (black circles) or in response to MISO load (orange squares). The response generally matches the footprint of ISOs, with generators in states such as Nebraska responding to variation in SPP load, and generators in states like Illinois responding to variation in MISO load. Horse-race regressions are used to determine to which ISO’s load the generator is dispatched, following equation (5) in the main text.

collect the estimated  $\hat{\beta}$  coefficients, and I examine whether  $\hat{\beta}_{SPP}$  or  $\hat{\beta}_{MISO}$  is larger for each power plant. That is, is each power plant dispatched more in response to demand in its own ISO or in the neighboring ISO.

Figure 3 maps the location of each power plant, with separate markers to show whether the plant is dispatched at higher levels of generation more in response to SPP load (grey circles) or to MISO load (orange squares). The response matches the footprint of each ISO, with Western generators being dispatched in response to SPP load and Eastern generators in response to MISO load. It is worth noting that the MISO service territory extends northwest into North Dakota and Montana; the SPP and MISO footprints are intermingled in those states.

Appendix Table A3 shows that 91 percent of SPP plants have  $\hat{\beta}_{SPP} > \hat{\beta}_{MISO}$  and 84 percent of MISO plants have  $\hat{\beta}_{SPP} < \hat{\beta}_{MISO}$  – the large majority of power plants are dispatched more in response to load within their own region. The remaining 9-16 percent of power plants that respond to *other* ISO load tend to have results estimated with less precision. The Appendix shows a map comparable to Figure 3 but where markers are sized according to the t-stat on the difference in the two coefficients. That map shows that power plants responding to the “wrong” ISO tend to have smaller t-stats, reflecting either a smaller difference in the two point estimates or more noise in the estimation. The Appendix also shows that the 84 to 91 percent numbers are similar for alternative horse race specifications

Figure 4: Some Power Plants Are Dispatched More For Own-Region Load



Note: This figure shows whether power plants are dispatched at higher levels of generation in response to Northern (black X), Central (orange square), or Southern (grey circle) regional load within their own ISO. Within SPP (left panel), no clear pattern is detectable. In contrast, MISO generators (right panel) appear to respond more to nearby load than to far-away load.

and various weighting schemes.

I next extend the horse race regressions to examine the possibility of within-ISO constraints. Specifically, I break out demand into three regional variables – North, Central, and South – for each ISO. For power reasons, I do not include all six regional load variables in the horse race regression; rather, I include the three regional demand variables for a power plant’s own ISO, plus total demand in the other ISO, and total demand in the rest of the Eastern Interconnection. For a SPP-located unit, for instance, the regression is:

$$g_{i,t} = \beta_1 d_{NorthSPP,t} + \beta_2 d_{CentralSPP,t} + \beta_3 d_{SouthSPP,t} + \beta_4 d_{MISO,t} + \beta_5 d_{EI,t} + X_t \Theta + \varepsilon_{i,t} \quad (6)$$

Figure 4 displays whether each fossil power plant responds more to Northern (black X), Central (orange square), or Southern (grey circle) regional load within their own ISO. For SPP, the pattern is only weakly detectable. This is consistent with the results in Table 1, which showed that within-SPP constraints contribute very little to the annual allocative inefficiencies. In contrast, a clear pattern emerges within MISO, where power plants in the north (e.g. North Dakota) tend to be dispatched in response to shocks to northern load; plants in places like Illinois tend to be dispatched in response to central load, and plants in Louisiana in response to southern load. This is consistent with transmission constraints tending to bind *within* MISO, and can explain why the within-MISO allocative inefficiencies are a large contributor in Table 1.

Overall, these horse race regressions are useful for several reasons. First, they are a new way of demonstrating the role of grid constraints across space. In doing so, they provide additional empirical support for the argument that eliminating transmission constraints could improve grid outcomes by allowing power plants to respond to demand shocks in far-away regions. Second, they confirm what Table 1 shows: within-ISO constraints are important, not only across-ISO constraints, and this is particularly true within MISO. Finally, it is especially reassuring that the stories that emerge from Figures 3 and 4 closely match the overall story of Table 1, because the methodologies I use are very different. The maps rely on hourly horse race regressions that are agnostic about the regional location of individual power plants and instead leverage hour-to-hour variation in demand across space. The allocative inefficiencies results in contrast rely on a constructed market equilibrium based on marginal costs and on NERC-defined geographic regions. Yet the two methods tell the same story about the importance and rough location of geographic constraints across and within ISOs.

## **5 Political Economy Implications: Some Producers Gain and Some Lose**

I have thus far shown that power plant dispatch in the Midwestern U.S. is more costly than it would be in a world without curtailments and without transmission constraints. This is in line with evidence from other regions, including Texas and Chile (LaRiviere and Lyu, 2022; Gonzales, Ito and Reguant, Forthcoming). I have also shown that the magnitude of the resulting inefficiency has grown over time, becoming more policy-relevant with increasing curtailments and increasing fuel prices. I next turn to analysis of how eliminating curtailments and transmission constraints might affect individual power plants and their owners. In particular, I calculate net revenues for each power plant under a least-cost dispatch scenario versus a transmission-constrained and wind-curtailed scenario.

The literature to date on transmission constraints and renewables integration has focused on total allocative inefficiencies – the importance for society of reducing generation costs is clear. However, the literature has largely ignored the role of producer surplus at individual plants or individual firms. Yet understanding the impacts of better grid integration on individual firms is also crucial for policy analysis. Transmission planning is largely a consensus-based process, with opportunities for actors to hold up new transmission development throughout the transmission planning process (Davis, Hausman and Rose, 2023). For political economy reasons, then, it is important to understand the incentives of firms to push for or to block new transmission lines.

The counterfactuals described in Sections 4.1 and 4.2 yield predicted quantities generated at each power plant. I can also use those counterfactuals to calculate the equilibrium price, equal to the marginal cost of the marginal generating unit. I then calculate net revenues as the revenues minus fuel and other variable costs; this static analysis ignores fixed costs (equivalently, I assume that fixed costs are equal across my two counterfactuals). For each generating unit, I calculate net revenues in each of my sample hours. I then aggregate across generating units to the power plant level.

Before presenting results, I discuss how this net revenue variable relates to overall profits. Most importantly, the relationship between the two depends on whether the utility is an investor-owned utility facing rate-of-return regulation, or a merchant generator. Nationwide, capacity is roughly split between the two types. For merchant generators, net revenues have a direct impacts on profits. However, for vertically-integrated investor-owned utilities, which make up the majority of my MISO and SPP sample, the relationship is more indirect. It will depend on the complex negotiations between utilities and the state-level commissions that regulate them, as in, for instance, Lim and Yurukoglu (2018) and Gowrisankaran, Langer and Reguant (2024). These negotiations are over how prices are set and what profits are allowed.

There are three mechanisms through which my net revenues will be correlated with the profits of an investor-owned utility. First, the utility may be the residual claimant on some of the revenues earned from wholesale sales in excess of its retail-serving needs. Second, high prices and load pocket conditions can justify investments in new power plants, on which the utility can earn a rate-of-return. And finally, power plant run times can be correlated with the utility’s ability to keep past investments “used and useful” (Gowrisankaran, Langer and Reguant, 2024). When assets like power plants are not “used and useful,” regulatory commissions may reduce the allowed returns for investors. Thus even when the utility is not the residual claimant on excess net revenues in the short-term, it can benefit from being in a load pocket by being able to justify new investments and delayed retirements.

## **5.1 Incentives to Block Transmission Increase as Renewables Enter**

As shown in Section 4.3, the allocative inefficiencies from inadequate transmission have been rising over time, in part as a function of increasing curtailments of renewables. Relatedly, the incentives for incumbents to block new transmission lines are also increasing as new renewables enter. Integrating the market implies that those low-cost renewables can be exported to other regions, which can both displace fossil generation and also lower market

Table 3: Incentives for Conventional Generators in MISO South to Block Transmission Increase as Renewables Enter

	(1) Net revenues, transmission-constrained	(2) Net revenues, integrated market	(3) Change in net revenues from integration
Wind generation available, GWh	-1,214*** (233)	-4,825*** (303)	-3,612*** (304)
Observations	61,292	61,284	61,280
R <sup>2</sup>	0.62	0.78	0.23

Note: The unit of observation is an hour. The independent variable is the total amount of wind available across MISO and SPP, summing across actual wind generation and curtailed wind generation, in GWh. The dependent variable is net revenues, measured in dollars in an hour, aggregated across all conventional and nuclear plants in MISO South, a region without wind generation. Standard errors are clustered by sample week.

prices for the remaining fossil generation.

To understand the magnitudes of this, I focus on MISO South, a region with no wind generation. I regress net revenues at the hourly level (for all of MISO South generators aggregated) on the quantity of wind available across the MISO and SPP footprints. “Available wind generation” is the sum of wind generation that actually occurred and wind generation that was curtailed. I estimate three regressions, each with a different dependent variable: (1) net revenues in the transmission-constrained counterfactual; (2) net revenues in the integrated market counterfactual; and (3) the change in net revenues a firm experiences when the market moves from constrained to integrated.

This regression has a causal interpretation provided that total wind availability is a function of exogenous weather patterns, and that weather does not impact dispatch and net revenues except via its impact on wind (conditional on controls, noted below). There are two things to note about this. First, the regression takes wind generation as given, and as such it ignores the dynamic effects of transmission on wind capacity. I comment more on this below.

Second, because the regression is causal only if wind generation is uncorrelated with the error term, I must control for other impacts of weather on the grid, most notably total quantity demanded. I also control for other determinants of generator dispatch and prices: fuel prices and various time effects (month of year, day of week, hour of day). Table 3 shows the results.

Column 1 shows that as wind enters the market, net revenues at conventional generators in MISO South drop - for every 1 GWh of additional wind, net revenues at all fossil and nuclear plants combined drop by \$1,200. To put this magnitude in perspective, as hourly

wind (both generation and curtailments) increased from 10.9 GWh in 2016 to 25.9 GWh in 2022, the coefficient would imply that hourly net revenues in this region dropped by a bit less than one percent. However, had the market been integrated, that same increase in wind would have implied a drop in hourly net revenues of \$4,800 (Column 2). As wind has entered SPP and MISO North/Central, the losses from integration for MISO South generators have substantially increased.

It is important to recall that Column 3 of Table 3 understates the incentives for conventional generators to block transmission, because it does not capture the effect of new transmission on wind investment. That is, Table 3 takes wind availability as exogenous – but new transmission can incentivize new renewables development, as shown by Gonzales, Ito and Reguant (Forthcoming).

Of course, net revenues increase at wind generators as they are able to enter the marketplace and as they are able to export to non-windy regions (see Appendix). The political economy and regulatory questions, then, regard whether new entrants have an equal voice in the negotiation process for new transmission lines, an issue I return to below.

## 5.2 Winners and Losers Are Located in Different Regions

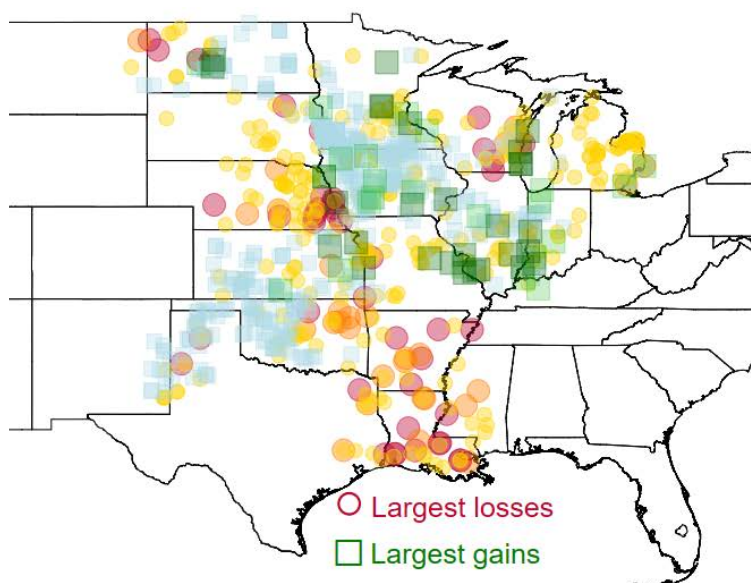
Figure 5 displays the location of each fossil, nuclear, and wind power plant in SPP and MISO, along with how net revenues compare under my two counterfactuals. Specifically, I calculate whether net revenues would rise or fall if transmission constraints and curtailments were eliminated. The plants that would lose the most (at least \$10 million in 2022) from eliminating transmission constraints and curtailments are shown in large red circles (a drop in net revenues of at least \$20 million) or orange circles (a drop between \$10 and \$20 million); the plants that would gain the most are shown with large green squares. Plants that are less affected are shown with smaller markers.

Consistent with Table 1 and Figures 3 and 4, there is a pronounced regional pattern. Plants in northern and central MISO and southwestern SPP stand to gain the most, and plants in southern MISO to lose the most. This regional pattern has political economy implications. Generation firms operating in southern MISO are not incentivized to develop new transmission lines that better integrate their power plants with the rest of the SPP and MISO footprints. In fact, these firms are likely to have financial incentives to block new lines – an incentive that has grown as wind has entered SPP and the rest of MISO.

The magnitude of the political economy problem is striking. The four firms that stand to lose the most collectively would have experienced a combined drop in net revenues of \$1.6 billion in 2022 alone, had the market been fully integrated and wind not curtailed. This is



Figure 5: Power Plants That Gain Versus Lose Are Located in Different Regions



Note: This figure shows whether individual power plants would win or lose if transmission across regions were increased and wind fully dispatched, rather than curtailed. Plants losing more than 10 million dollars per year, based on 2022 counterfactuals, are displayed in large red circles (a drop in net revenues of at least \$20 million) or orange circles (a drop between \$10 and \$20 million). Plants with a drop in net revenues of less than 10 million dollars are in small gold circles. Plants with net revenue gains of at least 10 million dollars are in large dark green squares (gains greater than \$20 million) or light green squares (gains between \$10 and \$20 million), and plants with smaller net revenue gains in small blue squares.

equal to three quarters of the total allocative inefficiencies for 2022. In other years, the net revenue drop for the four most affected firms would have been smaller in *level* terms, but it would still have been comparable in magnitude to the allocative inefficiencies in each year.<sup>27</sup> Thus while the literature to date has focused on allocative inefficiencies, I argue that the magnitude of potentials gains and losses at individual firms is just as important.

I can also calculate which firms stand to win from better integration, I find that they are primarily located in states like Iowa, Illinois, and Missouri.<sup>28</sup> Here, the four firms that stand to gain the most collectively would have seen net revenues of around \$1.0 billion more in 2022.

Wind generators as a group would have earned around \$0.8 billion more in 2022 under market integration. In Figure 5, they mostly appear as light blue squares: they individually gain, but the dollar values at any one site are relatively small simply because each plant has small capacity. Unfortunately, I do not observe full ownership data for the wind producers, so I cannot say precisely how large the losses would be at individual firms. The \$0.8 billion that I estimate they would gain is spread out across hundreds of wind sites. Taking the ownership data at face value, there are more than 300 utilities with wind generation in my sample – and thus the magnitude of gains to any single firm is small.

Importantly, though, my ownership data does not track parent firms of subsidiaries, a problem that is particularly acute for wind producers. Consider the case of NextEra, one of the largest wind owners in the country. Comparing the generation and capacity totals that NextEra reports on their website to national wind totals, we see that NextEra owns around 15 percent of all U.S. wind – and according to their map, a large fraction of their footprint is in MISO and SPP.<sup>29</sup> However in my data, their name only appears for around one percent of wind plants; the rest of their wind holdings are in LLCs, such as “Brady

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<sup>27</sup>While I have primarily focused on fossil power plants, these calculations also include net revenue changes at these firms’ nuclear plants. Nuclear plants are assumed to be baseload in my simulations, so relieving transmission constraints and removing curtailments does not change their quantity generated (and therefore the behavior of nuclear plants is not a source of allocative inefficiencies). It does, however, change the revenue received at these plants. Some of these four have sizeable nuclear capacity, although it is smaller than their fossil capacity.

<sup>28</sup>Again, I include non-fossil generation, and some of these firms have nuclear and/or wind capacity. Unfortunately, I do not observe wind generation disaggregated to individual locations; nor do I observe wind curtailments disaggregated across space. I allocate hourly regional (that is, SPP plus three broad regions within MISO) wind generation to individual firms based off annual totals reported in EIA-923, and I allocate curtailments based off ISO-level totals, the finest level of disaggregation I have. As discussed below, there are limitations in the wind ownership data: I do not observe parent firms; the calculations here ignore the possibility of subsidiaries and take at face value the ownership reported in EIA data.

<sup>29</sup>NextEra generation and capacity for 2020 are taken from <https://www.nexteraenergy.com/sustainability/overview/about-this-report/by-the-numbers.html>, accessed December 12 2023. National generation is taken from <https://www.eia.gov/electricity/data/browser> and capacity from <https://windexchange.energy.gov/maps-data/321>, each accessed December 12 2023.

Wind, LLC.” I do not have a comprehensive listing tying the many wind LLCs in MISO and SPP to their ultimate parent firm. (Note that 69 percent of the wind owners in my data have a name that includes the suffix “LLC,” whereas the comparable statistic for fossil owners is 17 percent.) Below, I discuss the political economy implications of wind’s potential gains from new transmission in light of these ownership patterns.

The other agents in the economy that matter here are of course electricity consumers. These consumers range from individual households to commercial and large industrial establishments. I have not presented consumer surplus estimates, as I do not know the physical location of different consumers (which would be needed to calculate the equilibrium price they face in different scenarios), nor do I model how wholesale prices are passed through to retail rates. However, in general one would expect consumers in load pockets to gain as their prices fall with market integration.

One caveat to bear in mind when analyzing Figure 5 (and the statistics in this section) is that the counterfactual net revenues at individual power plants will depend on the specifics of the dispatch model used, as well as the grid conditions (e.g. demand levels and fuel prices). Below, I conduct a variety of robustness checks. The specific dollar amounts vary across alternative counterfactual construction and across years. But below I show that the main takeaways for political economy purposes – the order of magnitude of net revenues changes in comparison to total allocative inefficiencies, as well as the geographic location of the firms – is quite stable.

### 5.3 Case Study: MISO South

The fact that the two generating firms standing to lose the most from grid integration in 2022 are in MISO South is not surprising – this area has long been known as a pocket with inadequate transmission ties to the rest of MISO. These two MISO South firms are Entergy Arkansas and Entergy Louisiana, both subsidiaries of Entergy, with my model showing integration leading to a combined \$930 million drop in net revenues in 2022. The history of the interactions between Entergy and MISO regarding transmission planning are particularly illuminating here. Entergy has a market value of over \$20 billion and has generation, transmission, distribution and retailing divisions across much of MISO South (including Arkansas, Louisiana, Mississippi, and Texas).<sup>30</sup> Most relevant, for more than a decade it has faced allegations of using both its own transmission system and the transmission planning process in MISO to prevent competition for its generation business.

Indeed, Entergy joined MISO in 2012 following a Department of Justice investigation

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<sup>30</sup>Market value is as of March 2023; source is [https://cdn.entergy.com/userfiles/content/about\\_entergy/pdfs/Entergy-fact-sheet.pdf](https://cdn.entergy.com/userfiles/content/about_entergy/pdfs/Entergy-fact-sheet.pdf), accessed December 18 2023.

into “allegations that Entergy has engaged in exclusionary conduct in its four-state utility service area... Specifically, the division has been exploring whether Entergy has harmed consumers by exercising its control over its transmission system and dominant fleet of gas-fired power plants to exclude rival operators of low-cost combined-cycle gas turbine (CCGT) power plants from competing to sell long-term power. In particular, the division has been evaluating whether Entergy’s practices have effectively foreclosed these more efficient rivals from obtaining long-term firm transmission service, a necessary input for selling long-term power products to wholesale customers in the Entergy service area. As part of the conduct investigation, the division has also been reviewing the competitive impact of, and circumstances surrounding, Entergy’s serial acquisition of rivals’ CCGT power plants” (Department of Justice, 2012). Entergy joined MISO, but has since been accused of stalling the MISO transmission process, again to protect its fossil plants.

The recent accusations against Entergy are instructive. First, watchdog groups and green advocates have argued that Entergy tries to throw wrenches in the transmission planning process (Tomich, 2021); this is what one might predict in a planning process where incumbent generators have a seat at the table (Davis, Hausman and Rose, 2023). Relatedly, one group has claimed that “Entergy secretly placed a consultant to advance its interests in MISO stakeholder meetings under the guise of a ‘MISO South customer’;” the watchdog group argues this may have been part of an attempt to prevent integration of wind generation by competitors (RTO Insider, 2020). Finally, twice Entergy has built new fossil plants, in part justifying the investment costs by pointing to transmission constraints, and then subsequently argued that new transmission lines were no longer needed (Kovvali and Macey, 2023; Howland, 2023). While Entergy as an investor-owned utility may not be the residual claimant on all net revenues from the wholesale market, these actions would be consistent with a desire to protect the rate base going forward.<sup>31</sup>

One caveat is that some of the most vocal opponents of Entergy have been renewable energy stakeholders, who may stand the most to gain from grid integration. Industry reports cite the Southern Renewable Energy Association as stating “Entergy appears to be using an anti-competitive strategy of capturing, delaying, and/or canceling transmission projects with local generation assets at significant cost to local ratepayers, while at the same time, not resolving underlying load pocket problems” (Howland, 2023). One might decide to take the accusations against Entergy with a grain of salt given the incentives of renewable energy stakeholders. On the other hand, it may be that in this case the incentives of renewable developers better match what would be optimal for society.

A related question is how the potential winners from grid integration behave in the trans-

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<sup>31</sup>The rate base refers to the firm’s investments, on which it is allowed a rate-of-return profit.

mission planning process, and whether they are incentivized to and capable of pushing for the build-out of new interregional lines. Recall that the primary winners are existing wind generators that would be curtailed less and would see higher wholesale prices, new wind entrants, and the consumers in load pockets who would see lower prices. The anecdotes above suggest that renewables are collectively pushing for new transmission projects. However, renewables firms and consumer advocates face two potential barriers: first, legal analysts have argued that the transmission planning process favors incumbent producers and disadvantages ratepayers, and it is possible that potential losers are more effective at lobbying than potential winners.<sup>32</sup> Klass et al. (2022) in particular argue that regional transmission organizations (RTOs) favor incumbent interests in a variety of ways: a result of the fact that RTOs are voluntary, so incumbents can threaten exit, and the fact that large utilities tend to have the most voting authority (rather than state governments, consumer advocates, or other interested parties).

Overall, I argue that understanding the political economy of new transmission lines is just as important as understanding the potential gains in allocative efficiency. There are many tactics an incumbent firm might use to protect its generation assets, as the MISO South case studies show, and the financial incentives to do so can be tremendous. Ultimately these incentives depend on the mix of generation, transmission, distribution, and retailing that a firm owns and operates – a utility that is a net purchaser of generation and primarily engages in distribution and retailing may have an incentive to seek out low-cost generation. It also depends on whether the utility is price-regulated, and if so, what relationship it has with a utilities commission. And I am aware of no reports like those regarding Entergy that have emerged for other utilities in my sample whose generation assets would be worth less under a more integrated grid. Nonetheless, the results in this section suggest that the current planning process is problematic given the fact that market integration is expected to bring very large losses to some incumbents.

## 6 Robustness Checks

In this section I evaluate whether the results above are similar under alternative assumptions about market equilibria. In particular, I allow for changes in: the definition of regional

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<sup>32</sup>For instance, Meng and Rode (2019) find “that firms that are expected to lose [from cap and trade] are more effective at lobbying to lower the policy’s chances than firms that are expected to gain are at lobbying to raise the policy’s chances.” Separately, Colgan, Green and Hale (2021) argue that “policymakers are loath to harm important economic assets even if asset holders do not proactively defend them.” It is plausible that this would be asymmetric in the sense that it would not show up as an equal desire to protect e.g. new entrants.

transmission constraints; the sample composition; the capacity of the generating units; the marginal cost of the generating units; the inclusion of engineering constraints; and the definition of the equilibrium price. I also look at what might happen in a future with more wind capacity. For each robustness check, I re-construct the market equilibria in every hour. In this section, I show that the reported annual allocative inefficiencies are comparable across all the robustness checks. I also show that across these robustness checks, gains and losses at individual firms are large.

## 6.1 Alternative Assumptions Used for Robustness Checks

I begin by describing why each robustness check is useful. First, and most importantly, I construct two alternative definitions of regional transmission constraints. My primary specification uses NERC subregions (map in Appendix). In the first robustness check, I use a much more conservative definition: I construct simply three regions: SPP, MISO North/Central, and MISO South. I use these three because they are readily apparent in the horse race regressions, above, as sources of congestion. This robustness check thus serves as a useful lower bound: it does not include constraints within SPP, or between North and Central MISO, for instance – it uses a more conservative assumption on the scope of subregional constraints.

I also allow for smaller regions to define the transmission constraints: rather than using NERC subregions, I use zones from the National Renewable Energy Laboratory’s ReEDS model (Cole et al., 2021). There are typically 1 to 6 zones per state in the ReEDS model (map in Appendix). The advantage of using these zones is that it allows me to pick up more localized transmission constraints than when I use NERC subregions. The disadvantage is that I may falsely attribute to transmission constraints *other* deviations from least-cost dispatch observed in the real world (e.g., an unexpected plant outage) that impact the overall generation in a ReEDS zone. (In contrast, when regional definitions are very broad, these deviations across space are more likely to be averaged out across plants, thus not impacting the overall generation in the region.)

Second, I change the sample composition by allowing units like combined heat and power units and industrial generators to participate in the market. In the main results, I follow the literature in assuming that the behavior of these units is driven by other considerations (for instance, the need to have steam for industrial processing), not by marginal revenue from the wholesale electricity market. I thus drop them from the sample of interest. However, in this robustness check, I include these units, constructing marginal cost curves as a function of heat rates, fuel prices, and O&M costs (just as I do for the main sample) and including

these units in my least-cost dispatch algorithm.

Third, I change the capacity and marginal cost of each generating unit by assuming that the unit's capacity is equal to its sample-wide maximum observed generation, rather than its yearly maximum observed generation. I similarly calculate the heat rate of each unit to be equal to its sample-wide heat rate, rather than its annual heat rate. This robustness check has the disadvantage of assuming that a unit with a capacity expansion partway through the sample was able to generate at that higher level throughout my sample. However, it has the advantage of capturing a higher capacity for units that operate very infrequently and may not have reached maximum capacity in any given year. My fourth robustness check also modifies maximum capacity: I partially derate capacity uniformly at all units, rather than stochastically applying outages.

Fifth, I modify marginal costs in several ways. In my main sample, I use sample-wide average markups to construct generator fuel costs. For natural gas, this markup does not vary much over time. However, the oil markup was higher in 2022, and so in this robustness check I use the 2022 markup. Next, I assume alternative variable operations and maintenance costs for combustion turbine generators; engineering sources are in disagreement about the magnitude of these costs. In my primary specification, I assume variable O&M of around \$5 for combustion turbines, following Energy Information Administration (2022). In two robustness checks, I instead use either \$0 or \$10, which essentially says that either none of O&M for combustion turbines is fixed (i.e., it is all variable), or all O&M is variable, where the bounds come from Table 8.4 of Energy Information Administration (2023).

Next, I construct robustness checks that incorporate additional engineering constraints not included in the primary least-cost dispatch model. In the first, I assume that there are unobservable constraints related to system-wide reliability, and that combustion turbines are dispatched to satisfy these constraints. Accordingly, I force the region-wide generation for combustion turbines as a whole to be equal to what I observe in the real world; similarly I force the region-wide generation for non-CTs (boilers and combined cycle units) to be equal to what I observe in the real world. That is, I allow least-cost dispatch *within* these technology groups. I include this constraint in both the integrated and transmission-constrained counterfactuals.

Alternatively, I assume that units operating below their minimum constraint in the real world were following some set of unobservable incentives or constraints, and I force their generation in both of my counterfactuals to be equal to what these units generated in the real world.

Finally, I construct equilibria prices in two alternative ways. In my main specification, I assume that the equilibrium price is equal to the marginal cost of the marginal generating

unit.<sup>33</sup> However some high-cost units may be dispatched because of reliability concerns or engineering constraints; as such they might not be compensated at their marginal cost, but rather receive payments in the ancillary services markets, or various forms of out-of-market payments. Thus in these two robustness checks, I instead set the equilibrium price at the marginal cost of the 95th or 99th percentile of dispatched fossil units.

## 6.2 Results for Robustness Checks

The annual allocative inefficiencies are remarkably similar under these alternative assumptions about market equilibria. In my main results, the allocative inefficiencies in 2022 add up to \$2.2 billion. In the robustness checks, the smallest value I calculate for allocative inefficiencies is for the scenario with only three broad regions defining the transmission constraints: \$1.5 billion. Recalling that this is a lower bound, it is remarkable that simply those three regional constraints contribute 70% of the inefficiencies. The largest value I calculate for allocative inefficiencies is for the scenario with transmission constraints defined at the ReEDS-zone level: \$3.9 billion. Recall that this scenario uses smaller regions, so it attributes more of the real-world deviations from least-cost dispatch to transmission constraints, which increases the estimated value of allocative inefficiencies.

I also calculate a high wedge for the scenario that includes combined heat and power and industrial units (\$2.4 billion); this is not surprising as this scenario includes more units and more total generation. I calculate a lower wedge (\$1.9 billion) when uniformly derating capacity rather than applying random outages; this is because of the convexity of the supply curve. Across the remaining robustness checks, I calculate allocative inefficiencies in 2022 ranging from \$2.1 to \$2.2 billion, very similar to main results. That is, the main results are not sensitive to a variety of alternative assumptions about marginal costs, about the behavior of combustion turbines, or about the behavior of units at or below their minimum constraint.

Above, I report that there are multiple firms that stand to lose substantial net revenues from integration, particularly in comparison to the allocative inefficiencies that the literature tends to focus on. In my main model, the four firms with the most to lose from integration would collectively have seen net revenues lowered by \$1.6 billion in 2022. Across robustness checks, this varies from \$1.1 billion to \$2.4 billion.<sup>34</sup>

Another way to evaluate the robustness of the claim that effects across firms are as

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<sup>33</sup>Mills et al. (2021) provide empirical validation for this modeling of equilibrium prices across multiple years and multiple markets in the U.S., including MISO and SPP.

<sup>34</sup>The \$1.1 billion change in net revenues is from the model using three broad regional definitions; the \$2.4 billion is from the model using ReEDS definitions; other robustness checks yield an estimate between those bounds.



important to understand as allocative inefficiencies is to count the number of firms that would experience a drop in net revenues equal to at least 10 percent of the society-wide gains from removing transmission constraints. Examining all of my robustness checks across all the years of my sample (98 different counterfactual comparisons in total), the median number of such firms across all 98 year/robustness combinations is seven.

Results for Entergy Arkansas and Entergy Louisiana are also fairly similar for these various robustness checks. In Section 5 above, I report that these two would have collectively seen net revenues lowered by \$930 million in 2022 under market integration. Across nearly every robustness check, their combined net revenue changes for 2022 are similar: ranging from \$810 million to \$1.3 billion.

I also examine who would win and who would lose if wind generation were higher than it is today. Without a dynamic entry model, I cannot predict *where* new wind would enter (as I discuss more below). However, I can assume that wind expands capacity in the same places as existing capacity, and examine how this changes the patterns and magnitudes of wins and losses for incumbents. When I increase wind capacity (by either 10 percent or 100 percent, allocated to the same locations as existing capacity), the results for winners and losers are quite similar – Entergy Arkansas and Entergy Louisiana remain the largest losers from transmission expansion, and the magnitude of their drop in net revenues increases.

The one robustness check with somewhat qualitatively distinct results for Entergy in 2022 is the one in which combustion turbine generation is determined by reliability needs. Here, I examine results where either (1) combustion turbines are still able to set the market-clearing price, at their marginal cost; or (2) I assume combustion turbines are paid via other payments, like ancillary services, and therefore do not set the market-clearing price. In the former scenario, Entergy Arkansas and Louisiana still on net lose, but at a smaller magnitude: combined drops in net revenues are only \$120 million. This is because in this scenario, prices are estimated to rise in MISO South. The two firms that lose the most in this scenario are instead located in Nebraska and North Dakota, and each experiences drops in net revenues of \$300 to \$400 million. In contrast, when I do not allow combustion turbines to set the equilibrium price, the results for Entergy are very similar to the main results, with combined drops in net revenues of \$1.1 billion. These two robustness checks should be viewed as thought exercise or bounds more than realistic scenarios – while some combustion turbines are plausibly dispatched for reliability services, it is not the case that they *all* are in all hours. And notably, while the magnitude of the Entergy losses is quite different in one of these two checks, the primary point stands: that individual firms experience drops in net revenues in the hundreds of millions of dollars annually, and that this is likely to impact their incentives to block new lines.

Overall, my main results follow the literature in terms of assumptions about marginal cost, capacity, and equilibrium prices. When I use alternative assumptions for various aspects of the counterfactuals, I estimate similar results in terms of total allocative inefficiencies and in terms of who gains and who loses. Thus it does not appear that any of these results are an artifact of my assumptions about the MISO and SPP markets.

## 7 Conclusion

This paper leverages rich data across a broad part of the midwestern United States to understand the potential gains from improved market integration as well as the potential barriers to this integration. I study a time period (2016-2022) where wholesale electricity markets are rapidly changing as new renewable generators enter the market, which provides a policy-relevant context for understanding the current landscape for transmission infrastructure. I document several key facts.

First, I show that there are allocative inefficiencies in midwestern United States electricity markets stemming from transmission congestion that limits the ability of low-cost generators to participate in the market. Second, I show that these allocative inefficiencies were historically low but rose rapidly over 2020-2022, in part because of the rise of wind generation – and the wind curtailments that have resulted from transmission lines not keeping pace with new renewables builds. For 2022, I document more than \$2 billion from regional transmission congestion in the MISO and SPP markets. This is a lower bound as it does not include very localized transmission congestion, reliability impacts, or long-term investment impacts. Impacts into the future will also of course depend on the future paths of natural gas prices and curtailments.

Third, I show that while fossil net revenues have eroded as new wind has entered, fossil incumbents have been partly protected by transmission congestion. Put differently, as low-cost wind enters, the incentive for some fossil incumbents (those in load pockets) to block new transmission lines rises. We might thus expect incumbent opposition to new transmission to grow in parts of the country where it would open generators up to competition. Finally, the magnitudes of these incentives are large, with hundreds of millions of dollars on the line annually for individual firms.

Numerous analysts have pointed to flaws in the way transmission lines are planned, permitted, sited, and built in the United States. Davis, Hausman and Rose (2023) provide an overview; and Klass et al. (2022) and Macey, Welton and Wiseman (2023) detail the specific law and governance structures that impact grid reliability and transmission planning. Klass et al. (2022) write that “behind many of the current laws, tariffs, and practices that

impede a clean, reliable energy future lies an RTO-governance model where incumbents hold outsized sway and, at times, have structural interests against the build-out of clean energy” (pp 1062-3). Interestingly, they also argue that MISO and SPP have some of the *better* planning processes for interregional transmission planning and renewables integration, suggesting that the cases I study in this paper may understate the magnitude of the problem relative to other areas of the country.

Future research could expand on my results in several ways. First, I have not focused on emissions outcomes across my various counterfactuals. In most years, my main counterfactual predicts somewhat *higher* CO2 emissions had the market been integrated – but more important for emissions outcomes is the long-run effects on fossil plant retirements and on new wind entry.<sup>35</sup> A dynamic model, along the lines of Linn and McCormack (2019), Gonzales, Ito and Reguant (Forthcoming), or Gowrisankaran, Langer and Reguant (2024) could be used to study these questions. Relatedly, it should not be forgotten that another aspect of the transmission network is the interconnection queue for new wind sites, which has faced a related but separate set of problems (Rand et al., 2022; Johnston, Yifei and Yang, 2023; Mays, 2023).

Future research could also expand the scope of this analysis by incorporating reliability impacts, which I have not modeled here. The existing network does to some extent reflect the fact that grid operators have historically prioritized reliability when planning transmission upgrades. Nonetheless, some have argued that winter storms Uri and Elliott – in 2021 and 2022, respectively – have demonstrated the need for greater interregional transmission lines to storm-proof the grid (Goggin and Schneider, 2022; Goggin and Zimmerman, 2023), and it is possible that reliability benefits are as large, or even larger than, the allocative efficiency benefits I have quantified.

Finally, additional research on cases in which incumbent utilities may have blocked new lines would be useful both for understanding how widespread such cases may be and what governance reforms might better align transmission planning with the interests of society at large. Related work on climate policy has examined lobbying activity and campaign contributions in the U.S. and Europe (Holland et al., 2015; Meng and Rode, 2019; Rode, 2021). A challenge in the transmission case is that the activities of stakeholders may be harder to observe. Indeed, Macey, Welton and Wiseman (2023) argue that “major utilities play dominant roles within NERC, grid system operators, and the regional entities that implement many NERC standards. These unusual arrangements—a kind of nested and interwoven self-

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<sup>35</sup>In my sample, this is a result of coal displacing natural gas, combined with coal’s high and unpriced CO2 emissions. Eliminating curtailments reduces CO2 emissions, but the effect is smaller for my time period than is the coal versus gas effect.

governance—allow large, entrenched actors to implement their agendas across institutions in opaque and unaccountable ways” (p 7).

Ultimately, my results tie into crucial questions about who will win and who will lose in an energy transition, and how this impacts the political economy of decarbonization. As Colgan, Green and Hale (2021) write, “Climate change and climate policy are altering the value of assets, from real estate and power plants to the labor of fossil fuel workers. This process generates increasingly contentious political battles over which assets, professions, and communities will retain value or even survive at all” (p 587). The policy question becomes whether the current legal, regulatory, and policy-making procedures adequately represent the interests of society as a whole – or whether there are opportunities for those who stand to lose to bend the process to their will.

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# A1 Appendix

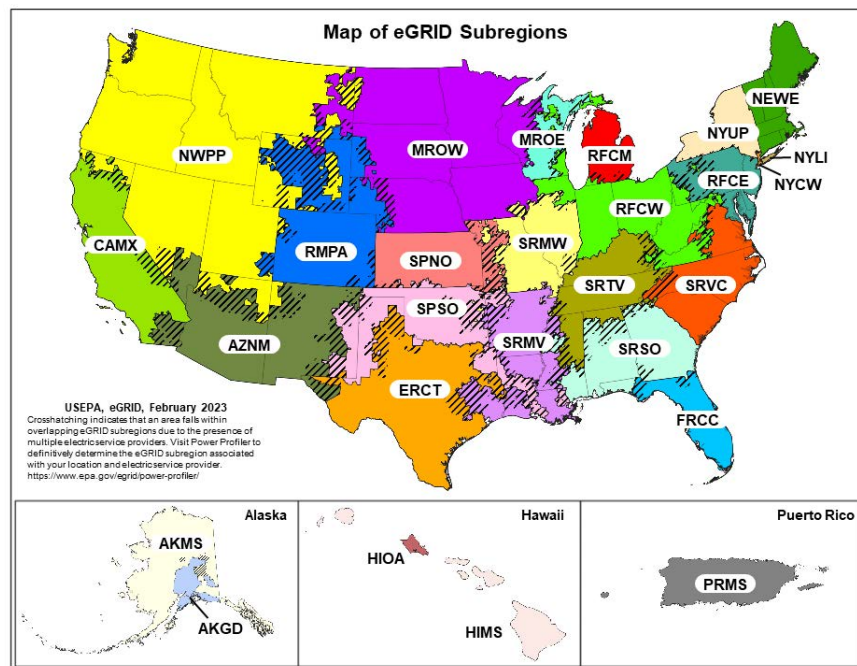
This Appendix shows additional tables and figures, referenced in the main text.

Table A1: Summary Statistics

	N	Mean	SD	Min	Max
Generator characteristics:					
Generation, MWh	53,339,178	71.1	149.3	0	890.9
Generation when dispatched, MWh	16,483,079	229.9	188.8	0.00096	890.9
Fuel type indicator: Coal-fired	53,339,178	0.21	0.41	0	1
Natural gas	53,339,178	0.74	0.44	0	1
Oil-fired	53,339,178	0.046	0.21	0	1
Coke-fired	53,339,178	0.0046	0.068	0	1
Technology indicator: Boiler	53,339,178	0.34	0.47	0	1
Combined cycle	53,339,178	0.15	0.36	0	1
Combustion turbine	53,339,178	0.51	0.50	0	1
Location indicator: MISO	53,339,178	0.66	0.47	0	1
Ownership indicator: IOU	53,339,178	0.92	0.28	0	1
Indicator: 1 if subject to ARP	53,339,178	0.86	0.35	0	1
Indicator: 1 if subject to CSAPR (SO2)	53,339,178	0.69	0.46	0	1
Indicator: 1 if subject to CSAPR (NOx)	53,339,178	0.95	0.21	0	1
Wind curtailed in MISO, MWh	27,030	535.5	722.1	0	4925
Wind curtailed in MISO, assumed where missing, MWh	61,326	441.1	514.5	0	4925
Wind curtailed in SPP, MWh	61,318	388.7	895.4	0	8953.9
Solar curtailed in SPP, MWh	8,752	0.71	6.23	0	126.1
Wind curtailment divided by wind generation, in MISO, MWh	61,325	0.072	0.100	0	4.13
Wind curtailment divided by wind generation, in SPP, MWh	61,257	0.028	0.054	0	0.71
National fuel prices:					
Coal, \$/MMBtu	61,326	2.34	0.16	2.04	2.65
Coke, \$/MMBtu	61,326	2.77	0.91	1.30	5.02
Natural gas, \$/MMBtu	61,326	4.37	2.12	2.29	18.5
Oil, \$/MMBtu	61,326	15.6	4.59	7.51	29.2
Market-wide quantities:					
Load (demand) in MISO, MWh	61,323	75735.3	12064.8	48827.3	121232.7
North MISO only	61,323	16843.2	2444.5	10772.1	26555.6
Central MISO only	61,323	39103.0	6709.5	23961.3	66434.4
South MISO only	61,323	19789.1	3754.4	11878.9	32612.0
Load (demand) in SPP, MWh	61,295	30478.4	5638.5	0	52954.7
North SPP only	61,287	7117.8	1174.3	4387.3	11744.9
Central SPP only	61,287	8595.0	1887.3	4425.9	15928.0
South SPP only	61,287	14769.6	2830.7	9714.0	26349.8
Load (demand) in the Eastern Interconnection, MWh	61,278	225436.8	40925.8	78857.8	393893.1
Generation by fuel type by ISO:					
Coal, MISO	61,326	28608.1	8005.8	0	49653.1
Natural gas, MISO	61,326	20518.4	7115.9	0	53013.9
Hydro, MISO	61,326	1190.4	582.6	0	3714.5
Nuclear, MISO	61,326	11111.9	1281.5	0	13446.7
Other, MISO	61,326	951.1	281.8	0	2263.5
Solar, MISO	61,326	160.1	450.5	0	3361.8
Storage, MISO	61,326	11.9	67.0	0	589.9
Wind, MISO	61,326	7492.0	4649.4	0	24089.7
Coal, SPP	61,300	11899.3	4259.5	0	23343.8
Oil, SPP	61,300	24.7	45.9	0	960.3
Hydro, SPP	61,300	1273.7	556.4	0	2765.9
Natural gas, SPP	61,300	6997.8	3624.2	0	23127.4
Nuclear, SPP	61,300	1852.5	517.3	0	2610.3
Solar, SPP	61,300	58.1	75.6	0	227.7
Waste disposal, SPP	61,300	10.9	1.91	0	19.1
Wind, SPP	61,300	8558.5	4740.9	0	22696.9
Other, SPP	61,300	28.3	6.45	0	114.0
Cooling degree days, Missouri	61,326	3.78	5.58	0	22
Heating degree days, Missouri	61,326	13.2	14.6	0	67

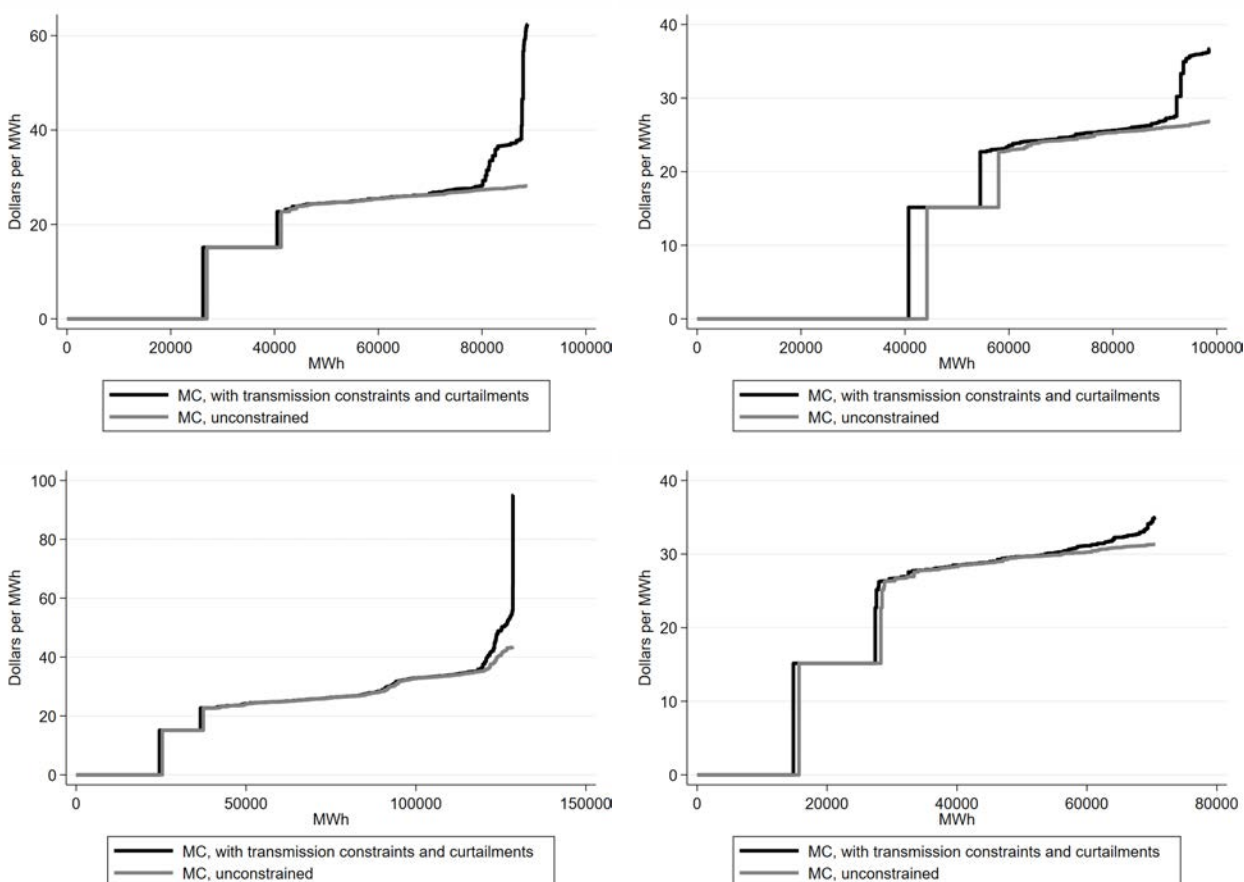
Note: This table provides summary statistics for my main estimation sample, at the generator by hour level. The sample is an unbalanced panel covering the period 2016-2022, with 993 generating units at 367 power plants. This represents all CEMS-reporting power plants (generally, fossil-fuel fired units with a capacity of at least 25 MW) in the MISO and SPP footprints. The main sample excludes commercial and industrial units and cogeneration units. There are fewer observations for the “quantity of wind curtailed” variables because the MISO reports this beginning in only December 2019, and because SPP data are missing for a small number of hours.

Figure A1: Subregion Boundaries



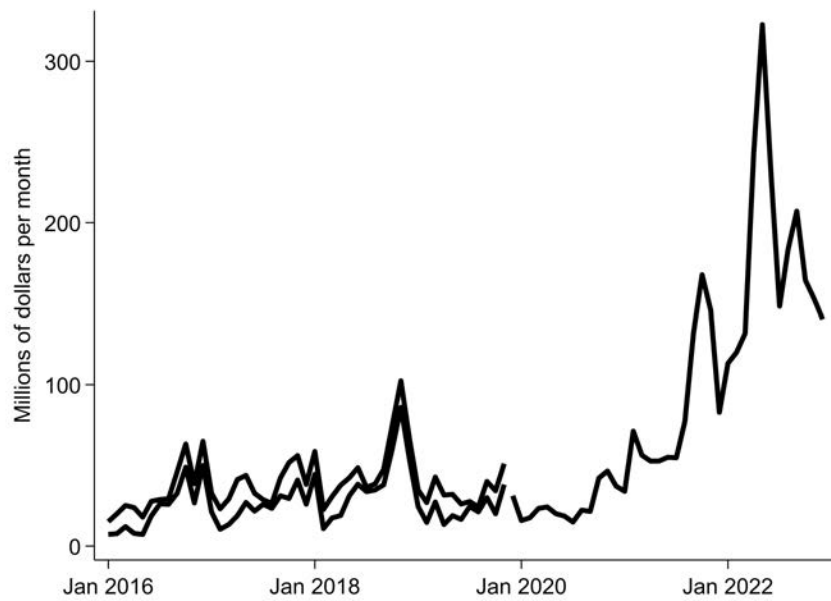
Note: This map shows subregion boundaries that I implement in my main transmission-constrained counterfactual. Map is from [https://www.epa.gov/system/files/images/2023-05/eGRID2021\\_subregion\\_map.png](https://www.epa.gov/system/files/images/2023-05/eGRID2021_subregion_map.png) or <https://www.epa.gov/egrid/maps>, accessed December 18, 2023.

Figure A2: Additional Example Marginal Cost Curves



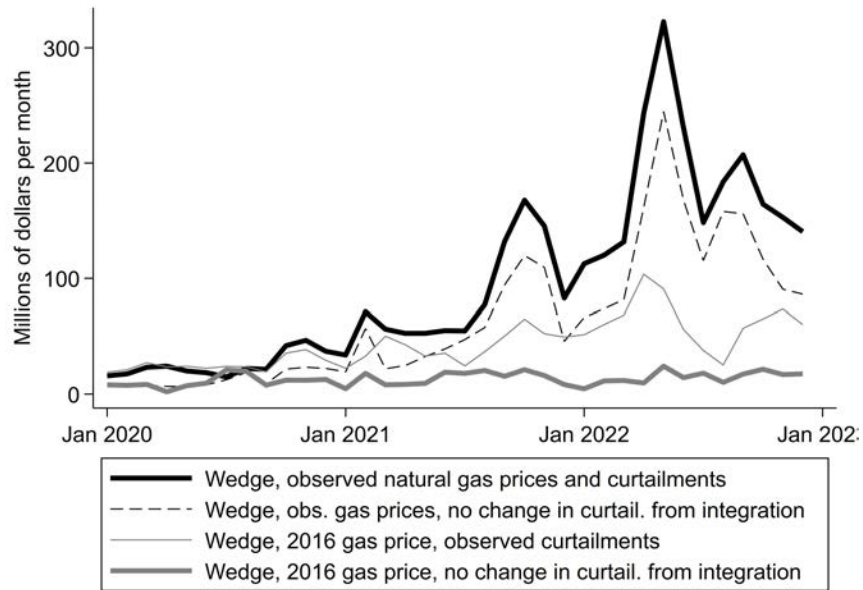
Note: This figure is constructed like Figure 1 in the main text, but showing alternative date-hour combinations. Note the scales of both axes vary across the four panels. The upper left panel shows an hour typical of the whole sample (2016 to 2022). The upper right panel shows an hour with particularly high curtailments (approximately two standard deviations above the sample mean for 2016-2022). The lower right panel shows an hour with high demand (two standard deviations above the sample mean), implying the dispatch of higher cost units. The bottom right panel shows an hour with low demand (two standard deviations below the sample mean).

Figure A3: Additional Generation Costs From Transmission Constraints and Wind Curtailments: 2016-2022



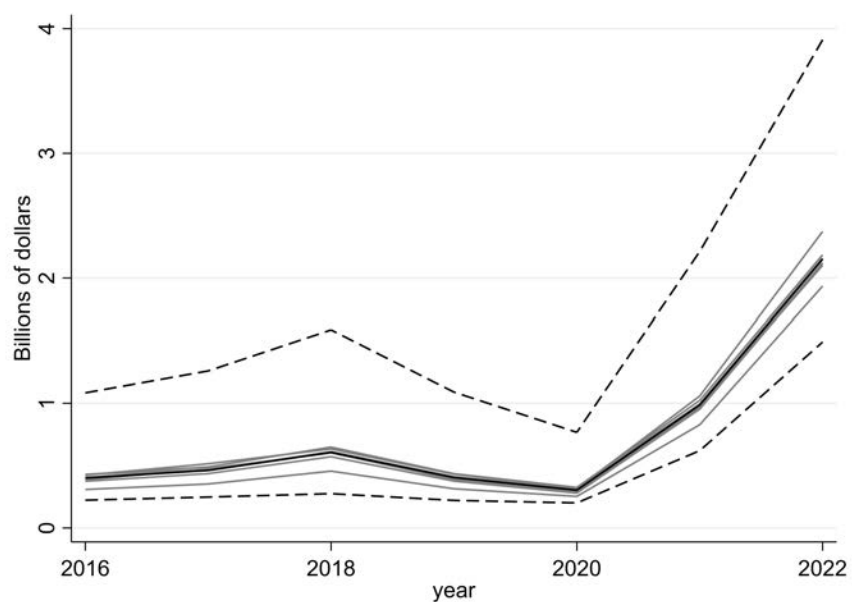
Note: This figure matches Figure 2 in the main text, but going back farther in time. For 2016 to 2019, curtailments are not observed. The two black lines for this time period show rough bounds. Specifically, the lower line assumes no wind was curtailed. In contrast, the upper line assumes the same quantity was curtailed as in 2020 – and allocating those curtailments across peak versus off-peak hours and across different months of the year to match the 2020 time profile. I use this as an upper bound because of general reports that curtailments have not fallen, and if anything have risen, over time.

Figure A4: Holding Gas Prices And/Or Curtailments Constant: Additional Generation Costs From Transmission Constraints and Wind Curtailments



Note: This figure matches Figure 2 in the main text, but with alternatives that hold natural gas prices and/or curtailments constant. The thick black line is the annual allocative inefficiency when calculated using observed natural gas prices and curtailments in both the constrained and integrated equilibria (i.e., it matches Figure 2). The dashed black line uses observed natural gas prices but assumes that wind curtailments do not change with market integration – specifically, it uses observed fossil generation in both counterfactuals. The thin grey line uses the 2016 average natural gas price for the whole sample, and it does change fossil generation between the counterfactuals by the amount of wind curtailed. The thick grey line uses the 2016 gas price, and assumes that wind curtailments do not change with market integration.

Figure A5: Robustness: Additional Generation Costs From Transmission Constraints and Wind Curtailments



Note: This figure matches Figure 2 in the main text, but collapsed to the annual level for simplicity and showing additional robustness checks. The thin black line in the middle is for the primary specification. The upper dashed line shows allocative inefficiencies when transmission constraints are measured at the ReEDS-zone level; the lower dashed line assumes transmission constraints only across three broad regions. Alternative robustness checks, detailed in the text, are shown with grey lines and closely match the main model.



Table A2: Alternative Specifications: Allocative Inefficiencies Increase as Wind Curtailments Increase

Panel A:						
	(1)	(2)	(3)	(4)	(5)	(6)
Demand	2.13*** (0.11)	1.06*** (0.08)	1.78*** (0.10)	1.77*** (0.19)	2.15*** (0.11)	
Load net of nuclear gen						1.87*** (0.10)
Natural gas price	1.26*** (0.10)	1.73*** (0.06)	1.19*** (0.09)	1.61*** (0.05)	1.38*** (0.10)	1.27*** (0.10)
Oil price	0.02 (0.16)	0.21*** (0.08)	0.02 (0.16)	0.13** (0.06)	0.02 (0.16)	0.03 (0.16)
Wind generation + curtailments	0.17*** (0.02)	0.33*** (0.02)	0.17*** (0.02)	0.20*** (0.02)	0.17*** (0.02)	0.17*** (0.02)
Observations	61,242	61,242	61,242	61,242	60,570	61,242
R <sup>2</sup>	0.73	0.64	0.73	0.73	0.74	0.73
Panel B:						
	(1)	(2)	(3)	(4)	(5)	(6)
Demand	2.13*** (0.10)	1.40*** (0.09)	1.82*** (0.10)	1.68*** (0.14)	2.13*** (0.10)	
Load net of nuclear gen						1.88*** (0.09)
Natural gas price	1.28*** (0.09)	1.68*** (0.05)	1.25*** (0.09)	1.50*** (0.04)	1.37*** (0.08)	1.29*** (0.09)
Oil price	0.09 (0.10)	0.15* (0.08)	0.09 (0.11)	0.04 (0.05)	0.09 (0.10)	0.09 (0.10)
Wind generation	-0.16*** (0.01)	0.03 (0.02)	-0.17*** (0.01)	-0.14*** (0.02)	-0.17*** (0.01)	-0.16*** (0.01)
Wind curtailments	0.27*** (0.01)	0.26*** (0.01)	0.27*** (0.01)	0.27*** (0.01)	0.27*** (0.01)	0.27*** (0.01)
Observations	61,008	61,008	61,008	61,008	60,387	61,008
R <sup>2</sup>	0.80	0.72	0.80	0.79	0.80	0.80

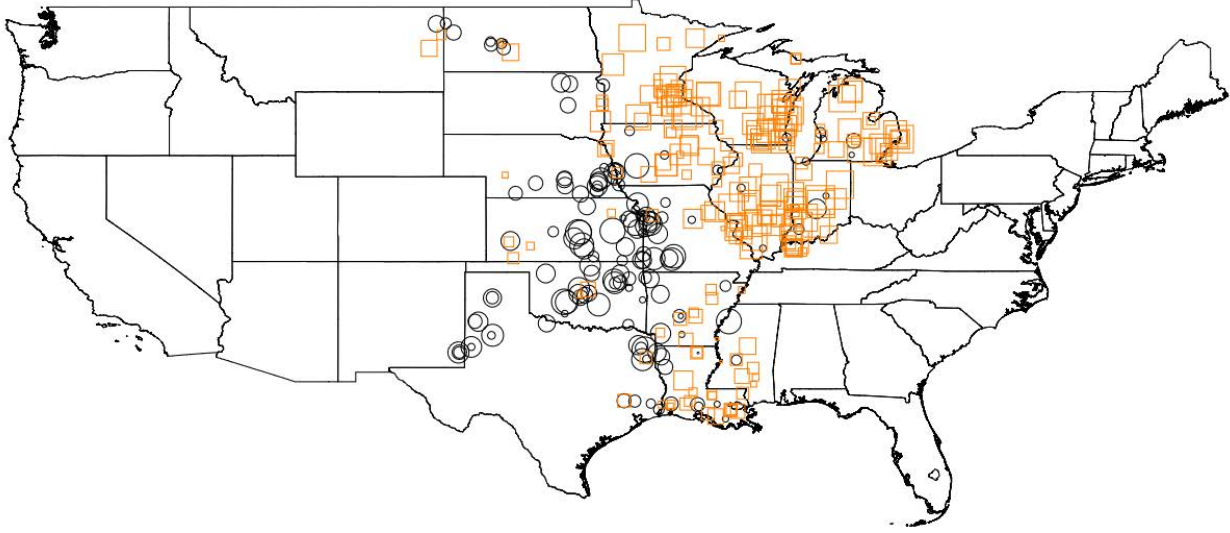
Note: Panel A of this table matches Column 1 of Table 2 in the main text, but with additional robustness checks; Panel B similarly matches Column 2. The first column recreates the results from Table 2. The second column drops the time effects. The third column drops the weather controls. The fourth column includes additional controls: specifically, all the two-way and three-way interactions of month-of-year, day-of-week, and hour-of-day controls. Rather than month-of-sample, it includes a linear time trend. The fifth column drops the period of Winter Storm Uri. The sixth column uses load net of nuclear generation, rather than load, on the right-hand side.

Table A3: Power Plants Are Dispatched For Own-ISO Load

	(1)	(2)	(3)	(4)	(5)	(6)
MISO	0.84	0.84	0.78	0.84	0.81	0.93
SPP	0.91	0.90	0.80	0.79	0.88	0.97

Note: This table shows the portion of power plants in each ISO that had a bigger coefficient on own-ISO load in the horserace regressions. The first row shows the portion of MISO-located plants ( $n = 243$ ), and the second row the portion of SPP-located plants ( $n = 121$ ). Column 1 shows the baseline specification. Column 2 includes the period of Winter Storm Uri in the horserace regressions. Column 3 drops controls from the horserace regressions (such as fuel prices, month effects, hour effects, and weather), but does control for load in the rest of the Eastern Interconnection. Column 4 weights observations in the table by the average hourly generation of the power plant over the 2016-2022 time period. Column 5 weights instead by the count of non-zero generation hours. Column 6 weights instead by the t-stat from the horserace regression.

Figure A6: Power Plants Are Dispatched For Own-ISO Load: Sized by t-stat



Note: This figure matches Figure 3 in the main text, but with markers sized by the t-stat on the difference in the coefficients on own-ISO and other-ISO load. That is, larger markers represent plants for which there is more certainty about the coefficient on one load being larger than the other. Power plants responding to *other*-ISO load tend to have smaller t-stats, reflecting either a smaller difference in the two coefficients or more noise in the estimation.

Table A4: Alternative Specifications: Incentives to Block Transmission Increase as Renewables Enter

	(1)	(2)	(3)	(4)	(5)
Wind generation available, GWh	-3612*** (304)	-3609*** (266)	-3291*** (276)	-3576*** (308)	-3194*** (292)
Observations	61,280	61,280	61,280	60,608	61,280
R <sup>2</sup>	0.23	0.23	0.17	0.24	0.22

Note: This table matches Column 3 of Table 3 from the main text, but for various alternative specifications. Column 1 recreates Column 3 of Table 3. Column 2 drops the weather controls. Column 3 drops the time effects. Column 4 drops the period of Winter Storm Uri. Column 5 includes more saturated time effects.

Table A5: Additional Results: Incentives to Block Transmission Increase as Renewables Enter

	(1) Net revenues, transmission-constrained	(2) Net revenues, integrated market	(3) Change in net revenues from integration
<b>Panel A: Net revenues, conventional gen.</b>			
Wind generation available, GWh	-1214*** (233)	-4825*** (303)	-3612*** (304)
Observations	61,292	61,284	61,280
R <sup>2</sup>	0.62	0.78	0.23
<b>Panel B: Net revenues, wind gen.</b>			
Wind generation available, GWh	22285*** (443)	27496*** (514)	5211*** (348)
Observations	61,292	61,292	61,292
R <sup>2</sup>	0.73	0.88	0.16

Note: This table expands on Table 3 from the main text. The dependent variable is net revenues, measured in dollars in an hour. The unit of observation is an hour. Panel A shows results for MISO South, an area without wind generators. Panel B shows results for wind generators across the entire SPP/MISO footprint. The independent variable is the total amount of wind available across MISO and SPP, summing across actual wind generation and curtailed wind generation, in GWh. Standard errors are clustered by sample week.

Figure A7: Robustness Check: Alternative Subregion Boundaries



Note: This map shows subregion boundaries from the ReEDS model, which I use to define transmission constraints in a robustness check.