NBER WORKING PAPER SERIES

POWER FLOWS: TRANSMISSION LINES, ALLOCATIVE EFFICIENCY, AND CORPORATE PROFITS

Catherine Hausman

Working Paper 32091
http://www.nber.org/papers/w32091

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2024, Revised January 2025

I am grateful to Tim Arvan, Max Auffhammer, Severin Borenstein, Jesse Buchsbaum, Charlotte Cavaille, Steve Cicala, Lucas Davis, Rob Gramlich, Dasom Ham, Josh Hausman, Stephen Holland, Koichiro Ito, Sarah Johnston, Devin Judge-Lord, Owen Kay, Julie Mulvaney Kemp, Alexandra Klass, Josh Macey, Erin Mansur, Johanna Mathieu, Dev Millstein, Michael Moore, Joachim Seel, and numerous conference and seminar attendees for helpful comments. All errors are my own. I do not have any financial relationships for this research. I received grant support in 2024 from Resources for the Future, for work on a related but independent project on transmission congestion. No party had the right to review this paper prior to its circulation. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 32091
January 2024, Revised January 2025
JEL No. L94, P18, Q41, Q42, Q48

ABSTRACT

Accelerated investment in electricity transmission could reduce total costs and enhance renewable integration. I document static allocative inefficiencies induced by incomplete market integration in two major U.S. markets; these have risen over time and totaled $2 billion in 2022. I also argue that estimating firm-level impacts is important, as incumbents may have the power to block new lines and other reforms. I show that four firms would have experienced a collective $1.3 billion drop in net revenues in 2022 had the market been integrated, and there are reports of some of these firms blocking transmission projects.

Catherine Hausman
Gerald R. Ford School of Public Policy
University of Michigan
735 South State Street
Ann Arbor, MI 48109
and NBER
chausman@umich.edu

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.

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 constraints on trade across regions, calculating the allocative inefficiencies caused by inadequate market integration. I also construct counterfactuals where the alleviation of constraints means that wind is no longer curtailed.[1]

I find that in the recent past, constraints on electricity trade across regions were not particularly costly, with static allocative inefficiencies averaging \$400 to \$500 million per year over the 2016-2020 period.[2] However the costs of these 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. I discuss, in light of this, what conditions in other regions and time periods would be expected to lead to high allocative inefficiencies. Moreover, as I discuss

[1] I do not directly distinguish between physical and institutional constraints (such as procedures governing the trade of electricity across regional markets). Much of the related literature has emphasized physical constraints, known to be a barrier to market integration, but below I also discuss the role of institutional constraints.

[2] Dollar values throughout are reported in \$2023; I deflate using the CPI from FRED.

below, there are additional costs on top of the \$2 billion: dynamic allocative inefficiencies, as well as reliability value.[3]

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). I also 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 across regions is very high.[4] 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 to disagreements over who pays for new lines.

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.[5] There is of course nothing problematic about these losses 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

[3]There are three dimensions to dynamic allocative inefficiencies. Gonzales, Ito and Reguant (2023) 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 in obtaining interconnections – impacts renewable development. And finally, transmission constraints may impact retirement decisions of existing generators.

[4]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).

[5]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 (areas with high demand and an insufficient ability to import power). Consumers in load pockets would also win. And finally, new renewables entrants could win as prices rise in windy areas, e.g., the Great Plains.

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 $1.3 billion less in net revenues in 2022. The majority of firms in my sample are rate-of-return regulated, and below 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 gap in the empirical literature on electricity market integration 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.[6] 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 (2023), 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 another major U.S. market. My paper complements their work by focusing on the across-region 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

[6]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, 2023; Johnston, Yifei and Yang, 2023; Kemp et al., 2023), but they generally do not investigate the impacts on incumbent fossil generators.

(2021); Fell, Kaffine and Novan (2021); Bloom et al. (2022); Doshi (2024); 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).

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), a point I return to below. The transmission network also has an important role in enhancing grid reliability (Borensten, Bushnell and Mansur, 2023). And 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).

Finally, my results relate to ongoing policy discussions about the state of the transmission network (and the fragmentation of regional electricity markets more broadly) and how best to manage the grid (Department of Energy, 2023*b*). These complex issues span economics, law, and engineering. I conclude the paper by tying my results back to these discussions.

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

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 (an "Independent System Operator," or ISO) 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.[7] MISO also covers fifteen states (roughly, from North Dakota to Michigan and south to Louisiana) and one Canadian province.[8] Some states are split between both

[7]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.

[8]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 Mon-

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.

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 competitive generation markets, as I describe below.

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 waste). Summary statistics and a map are provided in the Online Appendix. Most notably, wind generation is high (10 percent of generation in MISO and 30 percent in SPP over my sample), growing, and in different locations than conventional generators. Wind generation nearly doubled in MISO Central/North and SPP from 2016/17 to 2021/22. In contrast, MISO South has no wind generation. These changes over time suggest that the transmission network is not spatially suited to new market conditions. Wind generation increased by more than 10,000 MWh in the average hour in MISO Central/North and SPP in aggregate, and consumption changes over this time period did not offset this differential increase in supply.[9]

MISO and SPP have each seen new transmission capacity added during this time frame, but with limitations. As tables in the Appendix show, many transmission upgrades have been reported by the two ISOs over the 2016-2022 period, across a broad range of states. However, these projects were generally not intended to reduce generation costs related to congestion; the majority were aimed at addressing reliability needs, especially local and regional reliability.[10] Moreover, only three percent crossed state boundaries, and not a single project is listed as connecting MISO South with MISO North.

The data on MISO and SPP transmission upgrades in the Appendix points to why pre/post analyses of individual large-scale transmission projects, along the lines of what is done in Fell, Kaffine and Novan (2021); LaRiviere and Lyu (2022) and Gonzales, Ito and

tana and Texas) are only partly covered by MISO.

[9] Average hourly demand increased by around 680 MWh in MISO South and around 2,100 MWh in MISO Central/North plus SPP.

[10] Example descriptions of local and regional reliability projects make clear that these are not long-distance, high-voltage lines: "Install 69KV Breakers"; "Construct a new 69/25kV distribution substation"; "Construct approximately 0.5 mile in and out 115 kV line"; "Uprate ... 69 kV line to 115 MVA"; and "Rebuild 3.8-mile 115 kV line."

Reguant (2023), are not possible in this study's context – there is no individual project on the scale of something like Texas's CREZ project.[11,12] They also raise the question of why long-distance lines are not being built on a greater scale – which my results can help answer.

This paper focuses on the kinds of transmission build-out that would improve trade between MISO and SPP as well as across regions within each of the two markets. I do not address the possibility of greater trade with, e.g., the Western or Texas interconnections; nor do I address highly localized projects. Each of these different levels involve different costs and regulatory barriers (Davis, Hausman and Rose, 2023).[13] The level on which I focus has received attention by policymakers, in part related to the perception that interregional lines could lower generation costs but have faced regulatory and governance barriers.

Finally, in addition to physical transmission constraints, analysts have pointed to market design flaws and other institutional constraints limiting trade across ISOs. For electricity markets more generally across the U.S., there have been recent calls for both physical infrastructure improvements and greater market coordination across regions (Pfeifenberger et al., 2023; Energy and Environmental Economics Inc, 2024; Simeone and Rose, 2024).

3 Data

I build a 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 and hourly fuel use at individual thermal generating units;[14] a typical power plant has between one and eight generating units.[15]

[11] 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).

[12] One could imagine leveraging the time series of these projects. However, (1) the time series of dollars spent on the projects is nearly collinear with a linear time trend; and (2) the individual projects are each too small to yield much identifying variation, when compared to the size of the entire MISO/SPP market.

[13] In addition, utility incentives for encouraging versus blocking local transmission projects are very different than for interregional projects. Localized projects aimed at improving reliability do not subject the utility to a greater degree of competition on the generation side, in sharp contrast to longer-distance lines.

[14] 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). I then construct a conversion factor at the plant-by-technology level.

[15] 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

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).[16] I calculate each unit's capacity as the 99th percentile of observed generation. Generating units are taken offline frequently for maintenance, so I use seasonal 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 and renewable generation, as those fuel types are not represented in the CEMS data.[17] I also assemble wind curtailment data from the ISOs.[18] Each ISO also reports total quantity demanded at the hourly level (called "load" in electricity markets) for various regions.[19] 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).

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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 gas generation, according to the EPA's eGRID 2021 dataset.

[16] I generally allow heat rates to vary across years at the unit level, to reflect both unit degradation and capital improvements. Three plants have anomalous heat rates in just one or two years; for these, I use the sample-wide unit-level average.

[17] 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.

[18] Most ISOs across the U.S. report wind and/or solar curtailments. These are generally measured as the difference between actual generation and forecasted generation (for a very short-term forecast), conditional on the unit experiencing something like manual dispatch or a "follow flag." SPP's measurement, for instance, is described at `https://portal.spp.org/pages/ver-curtailments`. 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.

[19] MISO reports load across three broad regions (North, Central, and South). SPP reports more disaggregated regions – more than a dozen – which I aggregate to three broad regions to parallel the regional definitions I have for MISO.

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:

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

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 in natural gas and oil prices as well as the markup, so I construct fuel prices as the upstream price (varying daily) plus an annual state-level markup (the difference between the upstream and downstream prices reported by EIA). Coal prices have 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 Energy Information Administration (2022) and Energy Information Administration (2023*a*).

An additional, albeit 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.[20] 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 contains only the coal, natural gas, and oil power plants for which marginal costs are well-known. I drop the small number of thermal units with fuel types such as wood and municipal solid waste; these make up less than one percent of CEMS gen-

[20]Specifically, I calculate the annual 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.

eration. 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 market changes.

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.[21] For nuclear units, I assume a marginal cost based on the average operating expenses for nuclear units reported in Energy Information Administration (2023*a*).[22] I construct capacity for renewables and nuclear as follows. Maximum generation for renewables varies across hours, depending on weather (e.g. how windy it was that hour); I construct hourly maximum generation as observed generation for each fuel type, plus the quantity curtailed. I also assume that, because of their operational constraints, nuclear units will not respond to short-term fluctuations in wholesale prices (Davis and Hausman, 2016), and thus I fix their generation at what I empirically observe in each hour.

The other variable needed for 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. As explained in detail in the Appendix, I derate capacity across all units to account for planned outages, and I additionally stochastically remove units from the supply curve to account for unplanned outages. For computational simplicity, results reported in the main text use independent draws across each unit-by-hour observation. In the Appendix, I perform Monte Carlo simulations with each unplanned outage lasting two weeks, and results are similar.

With hourly marginal costs and annual capacities, I can construct market-wide marginal cost curves.[23] For my first counterfactual, I use a least-cost dispatch framework: I rank

[21]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. According to eGRID, 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).

[22]Table 8.4 of Energy Information Administration (2023*a*) reports average fuel costs of around \$8/MWh for my sample period. Operations and maintenance (O&M) costs average \$20/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 cost estimate of \$18/MWh, comparable to the California-specific estimate in Davis and Hausman (2016).

[23]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

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:

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

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).[24] 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.

The marginal costs of dispatched generators are 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 quantity curtailed for 2022; additional sample hours typical of different market conditions are shown in the Appendix. For this sample hour, 34,000 MWh of generation are provided by zero-cost renewables, an additional 13,000 MWh by nuclear, and the remaining 42,000 MWh 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.

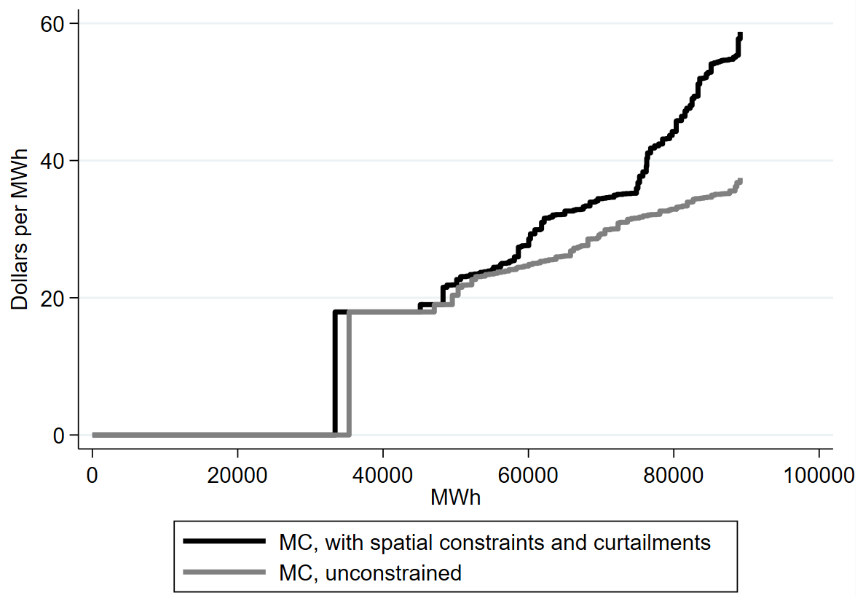
4.2 Modeling Spatial Constraints

For the second counterfactual, I assume that the system is constrained in two ways. First, I incorporate regional spatial constraints, modeled 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) and to MISO versus SPP as reported in EIA-860. I define subregions as the interaction between these two variables,

time with fuel prices and wind availability; thus one cannot simply assume an elasticity to back out the cost curve from a given observed equilibrium price and quantity.

[24] Note the terminology used varies; for instance, Mills et al. (2021) refers to this approach as a "fundamental supply curve model."

Figure 1: Marginal Costs of Dispatched Generators, With and Without Spatial Constraints (One Example Hour in 2022)



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 by ISO 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 \$18/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 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.

yielding ten subregions overall.[25] 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. As noted in the background section, I focus on this level of geographic constraint because transmission projects of roughly this magnitude (e.g. connecting two or three states, or crossing the MISO/SPP seam) have been the focus of much policy discussion in recent years (Department of Energy, 2023*b*, 2024).[26]

I infer 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.[27]

The optimization problem is thus:

$$\min_{g_{i,t}} \left(\sum_{i \in (1,2,\ldots I)} mc_{i,t} g_{i,t} \right) \quad s.t. \sum_{i \in (1,2,\ldots I_r)} g_{i,t} = obs\_gen_{r,t} \quad \forall r \in R;$$
$$g_{i,t} \leq C_{i,t} \quad \forall i; \tag{3}$$

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: $obs\_gen = \sum_{i \in (1,2,\ldots I_r)} g_{i,t}^{\text{observed}}$. Thus the *flows* of generation across regions cannot 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 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

[25] 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 spatial constraints might be to the ERCT, SRSO, and SRTV regions.

[26] An additional benefit of using NERC-by-ISO regions for the main specification is that it roughly corresponds to price hubs at the ISO level, so interpretation as a geographic area of interest for market outcomes makes sense; and my modeled equilibrium prices can be compared to ISO-reported prices (see Appendix). Nonetheless, robustness checks, below, model both a broader and a narrower set of geographic constraints for comparison.

[27] 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.

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 (related to the capacity of each line); detailed information on this topology is not publicly available. Furthermore, modeling the flow of electrons across the 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; Borensten, 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. In contrast, my setting features a complex set of interregional constraints. My reduced form model provides 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.

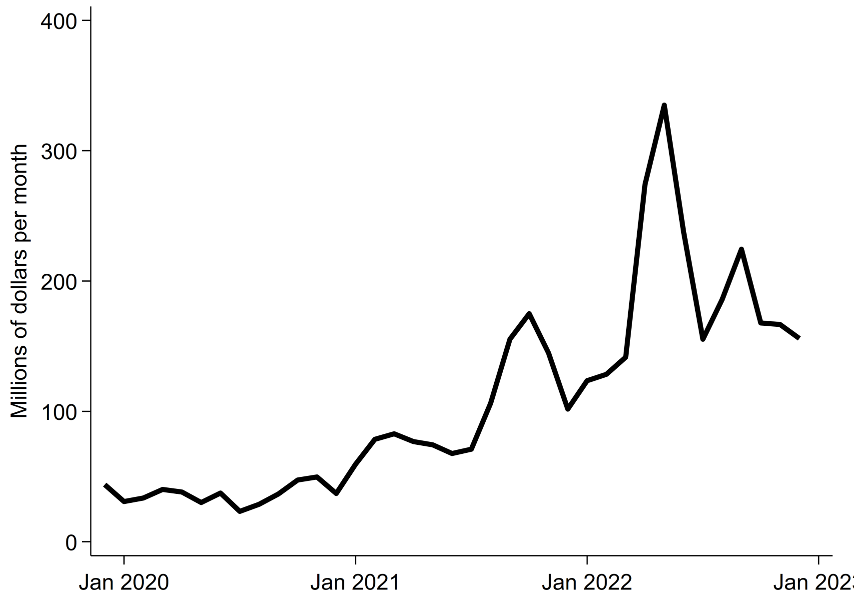
The marginal costs of dispatched generators for this second counterfactual are shown with the black line in Figure 1. Zero-cost generation shifts inward, by the quantity curtailed. Nuclear units are unaffected, by construction.[28] Also, some higher-cost thermal units must be dispatched because of the regional constraints.

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 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 $\sum_i mc_{i,t} g^{\dagger}_{i,t} - \sum_i mc_{i,t} g^{*}_{i,t}$, where $g^{\dagger}_{i,t}$ are equilibrium quantities from equation (3), and $g^{*}_{i,t}$ are equilibrium quantities from equation (2).

[28]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 Spatial Constraints



Note: This figure shows the monthly generation costs in MISO and SPP that arise from spatial constraints and associated renewables curtailments. Constraints are modeled at the NERC subregion by ISO 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 – the latter a result of spatial mismatch between supply and demand. Robustness checks are shown in the Appendix. Additional time series, holding various factors constant, are also shown in the Appendix.

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 spatial and curtailment-related allocative inefficiencies have been rising over time for the MISO and SPP markets. This is a combination of increasing natural gas prices and increasing curtailments – the latter induced by a growing spatial mismatch between supply and demand. By 2022, the average monthly allocative inefficiencies total \$190 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 \$0.8 to \$0.9 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 \$0.4 to \$0.5 billion dollars, and the 2021-2022 period, with annual inefficiencies of \$1.19 billion in 2021 and \$2.30 billion in 2022.

This stark difference in 2022 costs is primarily related to increasing natural gas costs and

Table 1: Annual Allocative Inefficiencies

Annual cost, billion dollars	2016-2020	2021	2022
Total	0.39 to 0.50	1.19	2.30
Across-ISO constraints	0.07	0.16	0.24
Within-ISO constraints	0.28	0.70	1.39
Curtailments	0.03 to 0.14	0.33	0.66
Within-SPP constraints	0.10	0.23	0.30
Within-MISO constraints	0.19	0.47	1.09

Note: This table shows the average annual generation costs in MISO and SPP stemming from spatial 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, constraints between MISO and SPP, and 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.

a growing spatial mismatch between supply and demand, 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):

$$c_t = \beta_1 d_t + \beta_2 w_t + \beta_3 n_t + \beta_4 o_t + X_t \Theta + \varepsilon_t \tag{4}$$

In the MISO/SPP context, increases in wind generation have not been spatially matched to demand. They have thus led to increases in curtailments, particularly in windy hours when capacity factors of wind generators are high.

I begin with *potential* wind generation, the sum of wind generation that made it to market and wind that was curtailed, on the right-hand side because it is exogenous (determined by weather rather than market activities); below I separately consider wind that was sold versus curtailed. 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). Coal prices are measured at the monthly level and are thus absorbed by the month of sample effects.[29] Overall, this regression is designed to describe how short-run shocks to demand, fuel prices, and wind generation correspond to allocative inefficiencies; it does not capture the extent to which medium-to-long run changes in the right-hand side variables lead to changes in investment decisions and therefore dynamic or long-run changes to allocative inefficiencies.

Table 2 shows the results; alternative specifications are shown in the Appendix. Not sur-

[29] In addition, coal prices are very stable over this time period and thus not likely to contribute to changes in the wedge over the sample.

Table 2: Allocative Inefficiencies Increase as Wind Curtailments Increase

	(1)	(2)	(3)	(4)
Demand	0.68***	0.69***	0.66***	0.68***
	(0.086)	(0.079)	(0.089)	(0.082)
Natural gas price	20726.7***	20643.9***	26789.7***	28261.0***
	(2894.8)	(3495.6)	(2742.8)	(2620.0)
Oil price	216.4	380.6*	204.3	424.5**
	(254.6)	(207.8)	(252.6)	(211.9)
Wind generation + curtailments	4.19***		4.51***	
	(0.22)		(0.28)	
Wind generation		1.09***		-0.14
		(0.12)		(0.17)
Wind curtailments		35.9***		46.6***
		(1.16)		(2.44)
Observations	61,266	61,266	56,854	56,854
R^2	0.79	0.86	0.34	0.53
K-P F-stat			168	16

Note: The unit of observation is an hour. The dependent variable is the hourly allocative inefficiency induced by spatial constraints. 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 week.

prisingly, the wedge is larger when demand is higher; the wedge is also larger when natural gas prices are higher.[30] Each additional MWh of demand implies \$0.68 in allocative inefficiencies in an hour. Going from the 25th percentile to the 75th percentile of demand would imply an increase in inefficiency of \$14,000 per hour (relative to an average hourly allocative inefficiency of \$98,000). Increasing natural gas prices by \$1 per mmBtu is correlated with a short-term increase in inefficiencies of around \$21,000 in an hour; note Henry Hub has a standard deviation of around \$1.7 per mmBtu over this time period.

The wedge is larger at times when potential wind generation is higher – as wind capacity has entered the market, it has led to an increase in spatial mismatch between supply and demand. 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 inefficiency increases. The implication is not that wind is not good for lowering costs, but rather that transmission is a complement to wind in the SPP/MISO markets, since wind generation is concentrated in low-population areas like Iowa and Kansas (see the map in the Appendix).

Combined, these results (Column 1) point to the conditions under which we might expect regional constraints to be costly in other regions and time periods. Positive demand shocks

[30]Oil generation is very small, so oil prices do not materially impact the wedge.

(for instance from new industrial growth or from increased electrification of the transportation sector) would be expected to increase allocative inefficiencies. And while natural gas prices fell in 2023, future natural gas price increases – or indeed any upward rotation of the supply curve – could again increase congestion costs. Extreme weather events leading to spatially-correlated plant outages would similarly increase the wedge. Finally, the increased presence of renewables in locations that historically had little power generation will lead to inefficiencies unless new transmission keeps up. Indeed, curtailments are rising in many regions of the country. Again, this does not imply that renewables themselves lead to inefficiencies, but rather that transmission is a complement to these technologies.

To expand on this point, Column 2 of Table 2 breaks total wind into two variables: generation that actually made it to market, and potential generation that was curtailed. The positive coefficient on wind comes almost entirely from curtailments, which in the SPP/MISO markets are primarily a function of transmission congestion. Spatial constraints that induce wind curtailments lead, over this time period, to more generation from fossil resources, implying an average increase in allocative inefficiencies of \$36 (Column 2). In contrast, wind generation that does make it to market corresponds to only a modest increase in allocative inefficiencies; presumably this arises because sometimes fossil generation that is located close to wind resources cannot be used, and more expensive and more distant fossil generation takes its place.

Curtailments are a function of system conditions, not just weather, so they are not exogenous. To the extent that they are the result of a combination of slowly-evolving wind capacity, of exogenous hourly wind shocks, and of slowly-evolving physical transmission infrastructure, they contain quasi-exogenous variation. Nonetheless, Columns 3 and 4 instrument for wind generation and curtailments using a vector of wind speed and capacity variables: wind speed at the hour-by-state level for each of the MISO and SPP states, and wind speed interacted with wind capacity in each state.[31] Results are similar to the OLS results from Column 2, and again make it clear that curtailments are indicative of transmission constraints that yield allocative inefficiencies over the sample period.

Additional tables in the Appendix explore heterogeneity in these results. In particular, the marginal effect of additional demand is especially large at high levels of demand, when the grid is more congested. Similarly, the wind effect especially matters at high levels of wind potential, when local congestion near wind sites is more likely and curtailments more common. These are not necessarily the same hours: in fact, demand and wind potential are negatively correlated ($r = -0.2$).

[31] Wind capacity is measured at the year level, and so its effect in *levels* is absorbed here by the month-of-sample effects.

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 fuel prices and/or curtailments constant.[32] It shows that the increase in allocative inefficiency in 2022 is a result of both changing fuel prices and rising curtailments (indicative of transmission congestion), with more of the effect coming from fuel price changes.

Low natural gas prices in recent decades had flattened the market-wide marginal cost curve for electricity. But with natural gas prices rising 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.

The rise in allocative inefficiency over my sample period has important policy implications. 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 demand in population centers. But in a world with more renewable generation, existing transmission lines do not match the spatial distribution of generation.

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 ($1.39 billion), whereas inefficiencies from across-ISO constraints totaled only $0.24 billion. The second largest component of inefficiencies was the need to curtail wind ($0.66 billion, row 4). With wind facing a marginal cost of essentially zero, curtailing it and having to use a fossil unit can significantly raise the costs of electricity generation.[33]

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

[32]In reality, curtailments in MISO and SPP are generally a function of transmission congestion, so it is not realistic to model transmission congestion as still holding while curtailments are eliminated. The thought experiment in the scenarios plotted in the figure is roughly: suppose the same quantity of wind (with the same hourly profile) had been built in the same locations where demand is served, such that it was unaffected by transmission congestion. The caveat, however, is that this hypothetical relocation of wind generation would also change the congestion patterns induced by the *non-curtailed* wind; whereas my decomposition assumes that the congestion patterns are unaffected by the relocation of wind.

[33]Decomposing into across-ISO, within-ISO, and curtailment effects is also useful if there are expansions of the transmission network that would change fossil dispatch without ameliorating all curtailments. If, for instance, 10% of curtailments cannot be solved with interregional transmission lines and instead relate to other reliability constraints, then interregional transmission lines would lead to improved allocative efficiencies totaling $2.23, rather than $2.30, billion dollars under 2022 conditions.

quantity of natural gas generation (nearly triple that of SPP's), combined with rising natural gas prices nationwide. I next turn to assessing model fit, and then to descriptive evidence of the sources of these spatial constraints.

4.4 Model Fit

This section assesses the extent to which the modeled outcomes match observable outcomes. Appendix A2 gives further details, including tables and figures, on what is summarized here. I show that generation quantities and prices both match observable outcomes well. Mean modeled generation in the constrained counterfactual exactly matches real-world generation, by construction. More informative is that the standard deviation and various percentiles are also close. Moreover, the correlation between observed and modeled generation is high, whether measured at the hour-by-unit level or at the cross-sectional level. Thus the model accurately predicts which units tend to get dispatched and which do not. The correlation is also very high for generation outcomes aggregated to the region by month by fuel and technology level, implying that the model does a good job of dispatching coal versus natural gas across space and time.

Observed and modeled prices also closely match. I collect hub-level locational marginal prices from both MISO and SPP, comparing these prices to the prices generated by my model. The average hourly price is very close (within two percent). This is remarkably close given that the model does not use actual price data in any way; rather, by making a few assumptions about marginal cost, spatial constraints, and market clearing, the model replicates the observed level of prices. Observed and modeled prices are also correlated, as expected, albeit at a lower level than are quantities. This is because steeply convex marginal cost curves push prices very high in some hours. Dropping outliers in both observed and modeled generation yields a much higher correlation. To ensure that the main results are not driven by these outliers, below I conduct a robustness check that winsorizes hourly prices.

In addition to assessing the level of prices, I assess the geographic dispersion of prices. This is an important indicator, as it reflects the presence of spatial constraints. Geographic dispersion in observed prices tracks the time pattern of price dispersion generated by the model, as well as the time pattern of the allocative inefficiencies reported above. This provides reassurance that the allocative inefficiencies reported above are indeed indicative of geographic constraints that lead to price separation across space. Similarly, I show that hours with a high degree of price dispersion also have a high level of modeled allocative inefficiency, and hours with a low level of price dispersion have lower allocative inefficiencies.

I next regress the price dispersion measure on demand, fuel prices, and wind potential, following equation (4) and Table 2 above. I show that all of these increase price dispersion, just as they increase modeled allocative inefficiencies. That is, allocative inefficiencies and geographic price dispersion depend in similar ways on market observables. Finally, I collect data from each ISO on the number of binding constraints in their dispatch algorithm, and on the shadow value of these constraints. I show that allocative inefficiencies are closely related to these binding constraints, providing reassurance that the modeled results reflect spatial constraints rather than other market inefficiencies.

Overall, the observed and modeled data match well, providing reassurance that the model accurately represents real-world conditions, and that the measured allocative inefficiencies are indicative of geographic constraints. I next assess the sources of these spatial constraints.

4.5 Sources of Spatial Constraints

Section 4.3 shows that total generation costs can increase substantially if generation is regionally constrained. In 2022, across-ISO and within-ISO regional constraints (ignoring curtailment effects) together added \$1.64 billion in generation costs for fossil units. Of this, the single largest source is within-MISO constraints (\$1.09 billion). To better understand these constraints, I turn to evidence on observed generator dispatch.

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 answer the question: do generators respond more to nearby or distant load (demand)? 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.[34]

For identification, 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:

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

[34] 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.

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. As noted above, 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).

With the assumption that demand is exogenous, additional control variables may not be needed to estimate 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 350 fossil plants in my CEMS sample,[35] with each regression using hourly data covering 2016-2022.[36] I then 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?

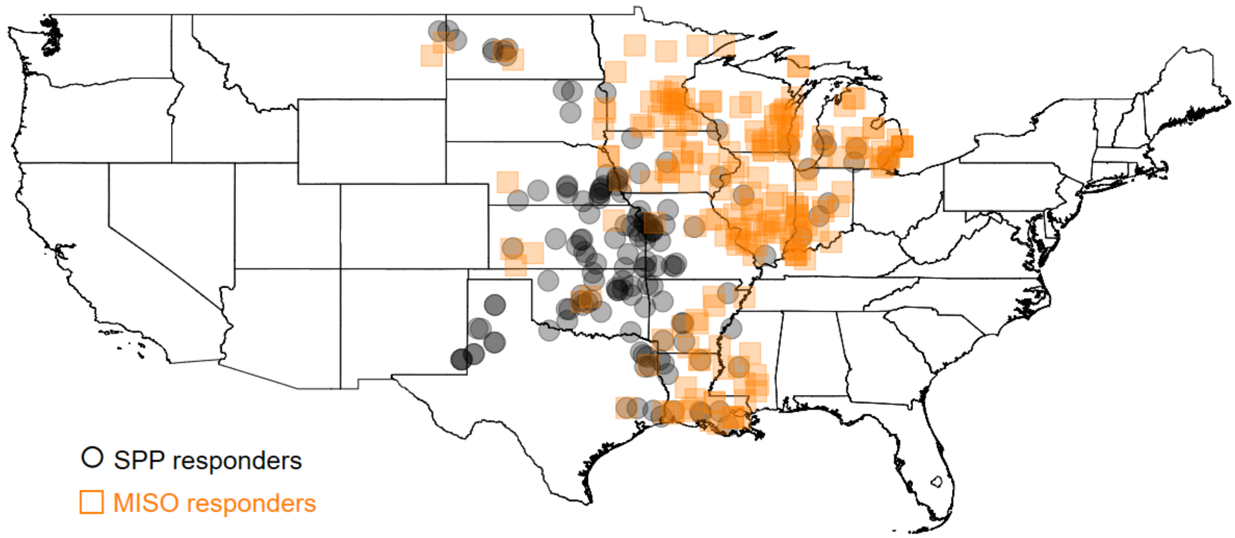
Figure 3 maps the location of each power plant, with separate markers to show whether the plant is dispatched at higher levels of generation more in response to SPP load (grey circles) or to MISO load (orange squares). The response closely matches the footprint of each ISO, with western generators being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

The Appendix 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 demand 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 ISO outside their region 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

[35] For statistical power, I collapse to the plant level, rather than the generator level. Also, I drop a small number of plants that generate very infrequently. I keep only units with at least 336 non-zero generation hours, equivalent to two weeks over my seven-year sample.

[36] The primary sample for equation (5) drops 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 (grey 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 text.

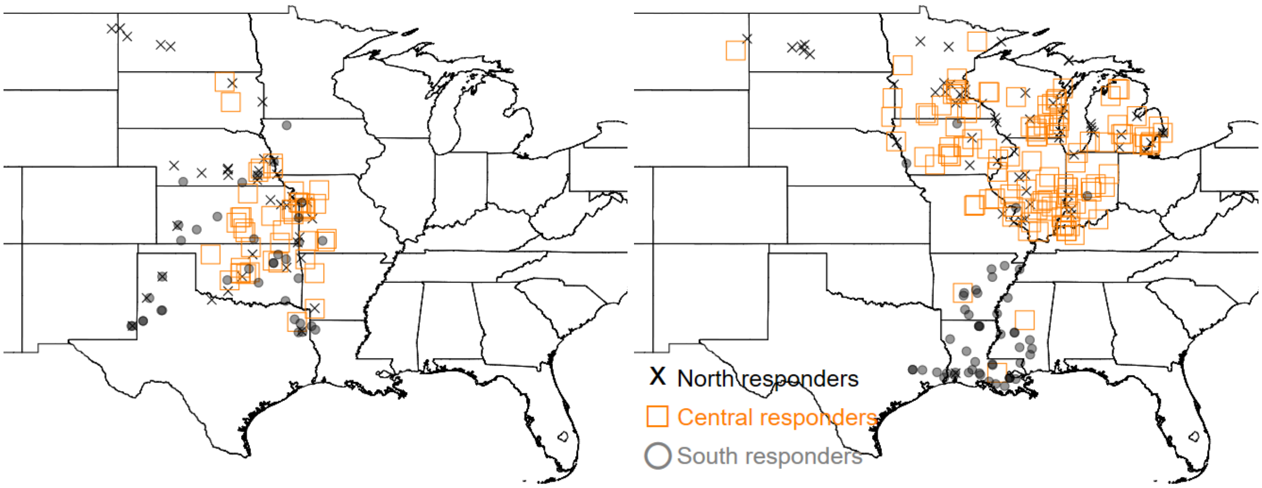
the 84 to 91 percent numbers are similar for alternative horse race specifications and various weighting schemes.

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 little to allocative inefficiencies. In contrast, in the MISO region, power plants in the north (e.g. North Dakota) tend to be dispatched in response to northern demand; plants in places like Illinois tend to be dispatched in response to central demand, and plants in Louisiana in response to southern demand. This

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.

is consistent with transmission constraints tending to bind *within* MISO, and it can explain why the within-MISO allocative inefficiencies are large in Table 1.

Finally, I conduct similar horse race regressions with prices as the outcome variable. Results are shown in the Appendix. Hourly hub-level prices tend to respond more to own-ISO demand shocks and also more to nearby regional demand shocks within their ISO.

The 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 empirical support for the argument that eliminating spatial constraints could improve grid outcomes by allowing power plants to respond to demand in different regions. Second, they confirm what Table 1 shows: within-ISO constraints matter, not only across-ISO constraints, and this is particularly true within MISO. Finally, it is reassuring that the stories told by Figures 3 and 4 closely match the overall story of Table 1, because the methodologies I use in each one are so different. The maps come from hourly horse race regressions that are agnostic about the regional location of individual power plants and instead leverage hourly variation in demand across space. The allocative inefficiencies results in Table 1, in contrast, come from a constructed market equilibrium based on marginal costs and on NERC-by-ISO-defined geographic regions. Yet the two methods tell the same story about the importance and rough location of geographic constraints across and within ISOs.

4.6 Market Power

I conclude these empirical results on allocative inefficiencies by discussing the role of market power. As Cicala (2022) notes, market power can be exercised by the withholding of generation from a unit, and this has been a focus of a strand of the electricity literature. In this section, I consider whether market power could produce the empirical results I observe. Both market power and transmission constraints can change how much electricity is generated in a region, so disentangling the two is important.

Suppose a generator withholds production to raise prices for other units owned by the same firm. If this occurs uniformly across all regions, it will not lead to the wedges I report. With inelastic demand, aggregate *regional* quantities would be unaffected, and my counterfactuals assume competitive bidding within each region.[37]

Next, consider a case where withholding occurs in some regions more than others. This is plausible if there are differences across regions in the marginal cost profile of generating units. Withholding would then lead to generation being less than a competitive counterfactual across an entire region, and my counterfactual would incorrectly model this as a transmission constraint.

It is implausible, however, that market power alone creates the allocative inefficiency I observe. First, there is geographic dispersion in observed market prices, as described in Section 4.4. This would not occur if there were market power being exercised in a geographically integrated market. Second, we observe generators responding to own-region demand more than other-region demand, as shown in Section 4.5. This will not occur with simple withholding in a geographically integrated market: the coefficients on own-region demand and other-region demand would still be expected to be equal. Instead, both observed prices and observed generation outcomes imply geographically distinct markets.

Third, it is usually argued that the U.S. electricity market is too large for market power to be sustained except where transmission constraints bind. As Wolak (2014) notes,

> There are a large number of electricity suppliers in the United States, none of which controls a significant fraction of the total installed capacity in the United States. Consequently, the market power that an electricity supplier possesses

[37]Note that a similar argument would apply if one were concerned that my results are an artifact of uneconomic dispatch by some units, as some analysts have alleged. Specifically, the claim has been made that some power plants, particularly investor-owned coal units, generate even when their marginal cost is above the price they receive, and that this reflects more than simply ramping or other dynamic constraints. I do not take a stand on whether this is true. But it will impact my results only if it is geographically concentrated, such that the regional quantity constraints I impose are affected. But crucially, the claims made in the existing literature apply across the MISO and SPP footprints (Daniel, 2017; Fisher et al., 2019; Daniel et al., 2020; Zimmerman et al., 2024).

> fundamentally depends on the size of the geographic market it competes in, which depends on the characteristics of the transmission network and location of final demand. (page 217)

That is, market power *enabled by* transmission constraints is plausible, but market power *instead of* transmission constraints is not. I return to this point below.

Fourth, both MISO and SPP are required to have a market monitor that screens for market power of various forms, and both ISOs have multiple market power mitigation procedures (Graf et al., 2021; Potomac Economics, 2023; Southwest Power Pool Market Monitoring Unit, 2023; Federal Energy Regulatory Commission, 2024). The market monitor knows the marginal cost of each plant and has multiple tests for deviations from marginal cost bidding (including evaluating plant outages, price mark-ups, output gaps, and whether individual suppliers are pivotal). Over my sample period, both market monitors have detailed annual reports with descriptions of how they screen for anticompetitive behavior, and both find that firms have behaved competitively in the vast majority of hours.[38]

Transmission constraints do make the exercise of market power more likely (Wolak, 2014; Graf et al., 2021; Potomac Economics, 2023; Southwest Power Pool Market Monitoring Unit, 2023; Federal Energy Regulatory Commission, 2024), so both market monitors specifically screen for this using multiple criteria. A load pocket can allow a local generating company to behave anticompetitively within that pocket, as competitors cannot physically supply to the area. This would indeed lead to observed regional generation quantities being smaller in the load pocket than what a competitive market would suggest; my model would pick this up as a transmission constraint. In that case, however, I would be *understating* the cost of the transmission constraint. The model assumes that units are dispatched according to least-cost within a region, and therefore does not pick up withholding or other monopolistic bidding within the region. Future research could look for evidence of local exercise of market power enabled by transmission congestion, but again, recall that market monitors and operators actively try to prevent this in MISO, SPP, and other regions.

5 Political Economy Implications: Some Producers Gain and Some Lose

I have thus far shown that power plant dispatch in the midwest is more costly than it would be in a world without curtailments and without spatial constraints. This is in line with

[38]Potomac Economics, (2017; 2018; 2019; 2020; 2021; 2022; 2023) and Southwest Power Pool Market Monitoring Unit, (2017; 2018; 2019; 2020; 2021; 2022; 2023).

evidence from other regions, including Texas and Chile (LaRiviere and Lyu, 2022; Gonzales, Ito and Reguant, 2023). 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 an analysis of how eliminating curtailments and spatial 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 regionally-constrained and wind-curtailed scenario.

The literature on transmission constraints and renewables integration has focused on total allocative inefficiencies. It 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 also matters 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 and other market integration reforms.

The counterfactuals in Sections 4.1 and 4.2 yield predicted quantities generated at each power plant. I can also use those counterfactuals to calculate equilibrium prices, equal to the marginal cost of the marginal generating unit. It is a market-wide price in the counterfactual without spatial constraints, and it is a vector of region-specific prices in the regionally-constrained equilibrium. 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. 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 Integration Increase as Renewables Enter

As shown in Section 4.3, the allocative inefficiencies from inadequate market integration 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 or other market integration reforms 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 prices for the remaining fossil generation.

To understand the effect of renewables on existing fossil generators, 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 potential wind generation across the MISO and SPP footprints. Potential wind generation is the sum of wind generation that made it to market and wind generation that was curtailed; recall that it is therefore exogenous to market activity. I estimate three regressions, each with a different dependent variable: (1) net revenues in the regionally-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 potential 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 so it ignores the *dynamic* effects of market integration 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 obviously demand. 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

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

	(1) Net revenues, regionally-constrained	(2) Net revenues, integrated market	(3) Change in net revenues from integration
Potential wind generation, GWh	-1,331***	-4,415***	-3,085***
	(241)	(283)	(284)
Observations	61,284	61,284	61,284
R^2	0.53	0.80	0.18

Note: The unit of observation is an hour. The independent variable is the total amount of potential wind generation 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.

nuclear plants combined drop by $1,300. To put this number 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 around ten percent. However, had the market been integrated, that same increase in wind would have implied a drop in hourly net revenues of $4,400 (Column 2). As wind has entered SPP and MISO North/Central, the losses from integration for MISO South generators have substantially increased.

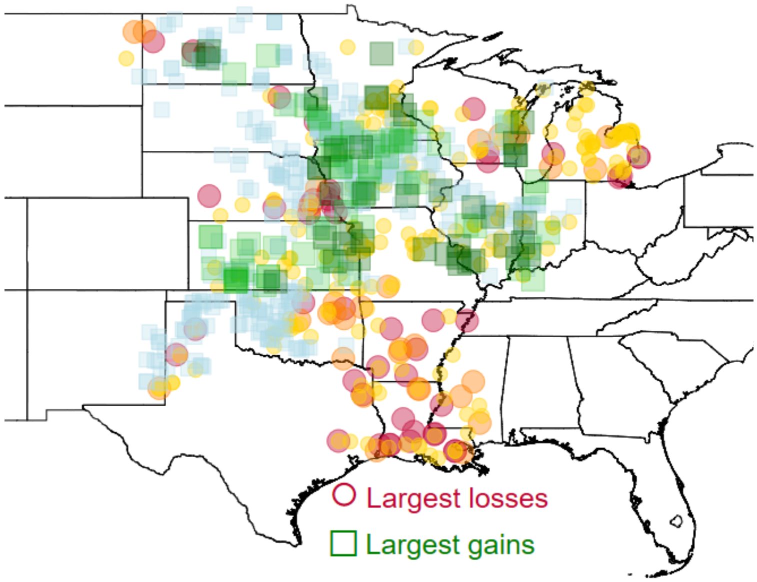
Recall that Column 3 of Table 3 understates the incentives for conventional generators to block transmission, because it does not capture the effect of new transmission on wind investment in the medium to long run. That is, Table 3 takes potential wind generation as exogenous – but new transmission can incentivize new renewables development, as shown by Gonzales, Ito and Reguant (2023).

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, relate to 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 spatial constraints and curtailments were eliminated. The plants that would lose the most (at least $10 million in 2022) from

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 spatial constraints across regions were eliminated 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 are in small blue squares.

eliminating spatial 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 would gain the most, and plants in southern MISO would lose the most. These patterns make sense given observed congestion in MISO and SPP; for instance, the Appendix shows a map of real-world annual average prices in 2022, with below-average prices in places like Nebraska, Kansas, southwest Minnesota, and Northwest Iowa, and with above-average prices in Michigan and MISO South.[39]

[39]The broad geographic patterns in Figure 5 and the prices map in the Appendix are similar. Some differences are that my measure of spatial constraints is less geographically fine-grained (thus ignoring, e.g.,

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.[40]

The magnitude of the political economy problem is striking. The four firms that stand to lose the most would have experienced a combined drop in net revenues of $1.3 billion in 2022 alone, had the market been fully integrated and wind not curtailed. This is equal to more than half 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 roughly comparable in relation to the allocative inefficiencies in each year.[41] Indeed, a time series in the Appendix shows that the magnitude of losses at these four firms is strongly correlated (over time) with allocative inefficiencies: as the potential gains to society have grown, so have the potential losses to these firms.

I also calculate which firms would win from better market integration; I find that they are primarily located in states like Iowa, Kansas, Minnesota, and Missouri.[42] Here, the four firms that stand to gain the most collectively would have seen net revenues of around $1.6 billion more in 2022.

Wind generators as a group would have earned around $1.7 billion more in 2022 with 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 gains would be at individual firms. The $1.7 billion that I estimate they would gain is spread out across hundreds of wind sites. Taking the EIA

congestion between Western and Eastern Kansas); and that my model does not capture some of the high prices that were seen in parts of RFCW in 2022.

[40]Note that reforms for market integration centered on institutional rules, rather than physical infrastructure, would face the same incentive problems.

[41]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 model, so relieving spatial 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 the four most affected firms have sizeable nuclear capacity, although it is smaller than their fossil capacity.

[42]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 on 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, as 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.

ownership data at face value (thus ignoring the possibility of subsidiaries), there are more than 300 utilities with wind generation in my sample – and thus the magnitude of gains to individual firms is small.[43]

Unfortunately, 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 nearly 15 percent of all U.S. wind. According to their map, a large fraction of their footprint is in MISO and SPP.[44] In my data, however, their name only appears for around one percent of wind plants; the rest of their wind holdings are in LLCs, such as "Brady Wind, LLC." I do not have a comprehensive listing tying the many wind LLCs in MISO and SPP to their ultimate parent firm. (In my data, 69 percent of wind owners 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.

Electricity consumers also matter. These consumers range from individual households to commercial and industrial establishments. I do not present consumer surplus estimates, since I do not know the physical location of different consumers (which would be needed to calculate the equilibrium price they face in different scenarios). I also do not 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 depend on the specifics of the dispatch model used, as well as the grid conditions (e.g. demand levels and fuel prices). Therefore, in Section 6, I conduct a variety of robustness checks. The specific dollar amounts vary across alternative counterfactual construction methods and across years. But the main takeaways for political economy purposes – the order of magnitude of net revenues changes in comparison to total allocative inefficiencies; and the broad geographic patterns – are quite stable.

[43]Note that the four firms for which I report the greatest drops in net revenue have very little wind capacity. The top two firms have no wind capacity according to EIA data and according to their website. The other two also primarily own conventional generators, although they each have some wind capacity.

[44]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.

5.3 Case Study: MISO South

That the two generating firms which would lose the most from grid integration in 2022 are in MISO South is unsurprising – 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 $850 million drop in net revenues in 2022. The history of the interactions between Entergy and MISO regarding transmission planning are illuminating. 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).[45] 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, 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. (Department of Justice, 2012)

Entergy joined MISO, but has since been accused of stalling the MISO transmission process, again to protect its fossil plants.

More recently, watchdog groups and green advocates have argued that Entergy disrupts the transmission planning process (Tomich, 2021), as one might predict in a planning process in which incumbent generators have a seat at the table (Davis, Hausman and Rose, 2023). One group 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 that this may have been part of an attempt to prevent competition from wind generation (Tait, 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

[45] Market value is as of March 2023; source is `https://cdn.entergy.com/userfiles/content/about_entergy/pdfs/Entergy-fact-sheet.pdf`, accessed December 18, 2023.

net revenues from the wholesale market, these actions are consistent with a desire to protect its rate base.[46]

A caveat is that some of the most vocal opponents of Entergy have been renewable energy stakeholders, who could be biased; they stand to gain the most from grid integration. One might decide to take the accusations against Entergy with a grain of salt given the incentives of renewable energy stakeholders. But the incentives of renewable developers may match what would be optimal for society, given a lack of nationwide carbon pricing.

A related question is how the potential winners from grid integration behave in the transmission 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 (1) existing wind generators that would be curtailed less and would see higher wholesale prices, (2) new wind entrants, and (3) the consumers in load pockets who would see lower prices. The anecdotes above suggest that renewable generators 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.[47] Klass et al. (2022) argue that regional transmission organizations (RTOs) favor incumbent interests in a variety of ways: a result of the fact that membership is 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). In the conclusion, I briefly discuss potential reforms.

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. 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. I am aware of no reports like those regarding Entergy that have emerged

[46]The rate base refers to the firm's investments, on which it is allowed a rate-of-return profit.

[47]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." And 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 policymaker preference would be asymmetric in the sense that it would not show up as an equal desire to protect e.g. new entrants.

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 would 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. I allow for changes in: the definition of regional constraints; the sample composition; the capacity of the generating units; the marginal cost of the generating units; the inclusion of engineering constraints; the inclusion of line losses; 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 constraints. My primary specification uses NERC subregions interacted with ISOs (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. This means a more conservative assumption on the scope of subregional constraints.

I also allow for smaller regions to define the spatial constraints: rather than using NERC subregions, I use zones from the National Renewable Energy Laboratory's ReEDS model (Cole et al., 2021) (again interacting them with the MISO versus SPP indicator). 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 broad, these deviations across space are more likely to be averaged out across plants, thus not impacting 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. 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 set 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. It has the advantage of capturing a higher capacity for units that operate infrequently and may not have reached maximum capacity in any given year. My fourth robustness check also modifies maximum capacity: I uniformly partially derate capacity across all units, rather than stochastically applying unplanned outages.

Fifth, I modify marginal costs in several ways. In my main sample, I use annual state-level markups to construct generator fuel costs. In an alternative version, I use a time-invariant national markup. Next, I assume alternative variable operations and maintenance costs for combustion turbine generators; engineering sources disagree on the magnitude of these costs. In my primary specification, I assume variable O&M of around \$5.4 for combustion turbines, following Energy Information Administration (2022) and Energy Information Administration (2023*a*). In two robustness checks, I instead use either \$0 or \$11.

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 regionally-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. This provides reassurance that ramping or other dynamic constraints do not drive the results.[48]

Next, I incorporate transmission line losses. According to the Energy Information Administration, around five percent of electricity is lost in transmission and distribution (Pacific Northwest National Laboratory, 2024).[49] I have not modeled these losses in my main analysis, as I do not have a representation of the physical grid. A key reason for improving the transmission grid is to reduce line losses (Southwest Power Pool, 2021; Department of Energy, 2023*b*); in that sense, transmission losses should be viewed the same as any other source of geographic constraint on the grid, and my model is an approximation of what would happen if they were eliminated. However to the extent that eliminating line losses is not feasible or not cost-effective, then my measured allocative efficiencies would be too large. To see this, I model a robustness check in which all quantity supplied after regionally-aggregated observed quantities are satisfied faces a five percent penalty on both marginal cost and on capacity, representing line losses.[50]

My next robustness check endogenizes congestion and curtailments. Rather than taking regional quantity constraints and curtailment quantities as given, I predict these variables as a function of hourly regional demand shocks, of regional wind capacity, and of wind speeds.

I next 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.[51] 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

[48]Another source of reassurance that dynamic constraints do not drive the results is that the allocative inefficiencies appear across all hours of the day (see Appendix). In contrast, generating even when it is statically uneconomic to do so is most likely at night, with generators staying on to avoid start-up or ramping costs when electricity demand increases the following morning.

[49]This five percent statistic overstates the amount lost in transmission; the bulk of this five percent likely occurs in the distribution system (Pacific Northwest National Laboratory, 2024). In MISO and SPP, the loss component of marginal prices is fairly small. Both ISOs report the component of locational marginal price dispersion that arises from congestion versus losses. Both components are approximately mean-zero, by construction; to see the relative importance of each, instead consider the standard deviation or the mean absolute standard deviation. By both of these measures, congestion is much more important than losses for MISO and SPP prices over my study's time frame.

[50]This robustness check ignores some nuances of line losses: in particular, they are larger when electricity is transmitted over long distances. Nonetheless, it can illuminate the extent to which line losses might be qualitatively important for my overall conclusions.

[51]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. I also show comparisons between modeled and observed prices in the Appendix.

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. I also add a robustness check in which I winsorize prices sample-wide at the 1st and 99th percentiles.

Finally, I construct counterfactuals in which market separation persists in most places, but where two adjacent regions are integrated. Some recent studies calling for expanded transmission have looked at large-scale integration across the U.S.; other studies have looked at build-out of just some key corridors (Brown and Botterud, 2021; Bloom et al., 2022; Department of Energy, 2023*b*; Goggin and Zimmerman, 2023*b*; Department of Energy, 2024). I conduct this analysis under two different sets of assumptions: assuming this integration solves the curtailments problem in both regions, or assuming it has no impact on curtailments relative to the original constrained equilibrium. A table and map showing the various regional pairs is in the Appendix.

6.2 Results for Robustness Checks

The annual allocative inefficiencies are similar under the alternative assumptions about market equilibria. In my main results, the allocative inefficiencies in 2022 add up to \$2.3 billion. In the robustness checks, the smallest value I calculate for allocative inefficiencies is in the scenario with only three broad regions defining the spatial constraints: \$1.5 billion. Recalling that this is a lower bound, it is striking that those three regional constraints alone contribute more than 60% of the inefficiency. The largest value I calculate for allocative inefficiencies is in the scenario with spatial constraints defined at the ReEDS-zone level: \$3.8 billion. Recall that this scenario uses smaller regions, so it attributes more of the real-world deviations from least-cost dispatch to spatial constraints, which increases the estimated value of allocative inefficiencies.

Across the remaining robustness checks, I calculate allocative inefficiencies in 2022 ranging from \$2.0 to \$2.5 billion, very similar to main results. That is, the main results are not particularly sensitive to a variety of alternative assumptions about the sample composition; marginal costs; the nature of outages; the behavior of combustion turbines; the behavior of units at or below their minimum constraint; line losses; or even predicting regionally-aggregated quantities using a vector of demand and wind variables.

Here I briefly summarize the results for integration of adjacent regions, rather than the entire market (the Appendix provides details). The largest gains from integration across two adjacent regions come from connecting MISO-SRMV to SPP-SPNO – that is, roughly Arkansas/Louisiana to Kansas/Missouri. That yields gains of around \$560 million under

2022 conditions, or roughly one quarter of the total reported in Table 1. Of the top gains from five pairwise combinations, three involve connecting MISO South to nearby parts of SPP. Thus the overall messages of the paper are corroborated with this analysis: cost savings from integration have been large in recent years, and MISO South is particularly isolated.

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 $1.3 billion in 2022. Across robustness checks, this varies from $1.0 billion to $2.5 billion. The specific firm identities of the four with the most to lose vary somewhat across robustness checks, but the geographic patterns are similar.

Consider a state-level aggregation of firms: across the more than 2,000 state by year by robustness check combinations, nearly 90% have the same sign (i.e. wins versus losses) as in the main results.[52] And, results for Entergy Arkansas and Entergy Louisiana are also similar in robustness checks. In Section 5, I report that these two would have collectively seen net revenues lowered by $850 million in 2022 under market integration. Across the robustness checks, their combined net revenue changes for 2022 are similar: ranging from $740 million to $1.1 billion. In the pairwise integration with the largest allocative efficiency gains, Entergy Arkansas and Entergy Louisiana again have the greatest revenue losses: $300 to $400 million dollars, depending on what one assumes about curtailments, or roughly 40-50% of the losses for the full integration counterfactual.

Another way to evaluate the robustness of the claim that effects on firms are as important as total allocative inefficiencies is to count the number of firms that experience a drop in net revenues equal to at least 10 percent of the society-wide gains from removing spatial constraints. In all robustness checks across all years of my sample (119 different counterfactual comparisons), the median number of such firms is five.

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. Instead, I assume that wind expands capacity in the same places as existing capacity, and I examine how this changes the patterns and magnitudes of wins and losses for incumbents. When wind capacity increases (by either 10 percent or 100 percent, allocated to the same locations as existing capacity), the results for winners and losers are similar – Entergy Arkansas and Entergy Louisiana remain among the largest losers from market integration, and the magnitude of their drop in net revenues increases.

[52]Moreover, in all states, the majority of robustness checks yield the same sign as in the main model. And in all robustness checks, the majority of states maintain the same sign as in the main model.

My main model follows the literature in terms of assumptions about marginal cost, capacity, and equilibrium prices. When I use alternative assumptions, I find similar results for total allocative inefficiencies and firm-level gains and losses. 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 United States to understand the potential gains from improved market integration as well as the potential barriers to this integration. I study years (2016-2022) when wholesale electricity markets were 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 resulting from spatial constraints that limit the ability of low-cost generators to serve 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. Existing low-cost wind power could serve more customers if there were more transmission capacity. For 2022, I document costs of more than $2 billion from regional constraints in the MISO and SPP markets. This is a lower bound, since it does not include very localized transmission congestion, reliability impacts, or long-term investment impacts. Future effects will also of course depend on the future paths of natural gas prices.

A sizeable reallocation of generation is possible just with pairwise integration of a few key regions. Moreover, calculations in the Appendix show that, compared to the magnitude of costs for a large transmission project (CREZ) in Texas, pairwise integration frequently passes a rough cost/benefit test.

Third, I show that while fossil net revenues have eroded as new wind has entered, fossil incumbents have been partly protected by regional constraints. Put differently, as low-cost wind enters, the incentive for some fossil incumbents (those in load pockets) to block new transmission lines (and other market integration reforms) 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. The magnitudes of these incentives are large: hundreds of millions of dollars annually for individual firms.

Others 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), Peskoe (2023), and Macey, Welton and Wiseman (2024) 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).

They also argue that MISO and SPP have some of the *better* processes for interregional transmission planning and renewables integration, suggesting that the cases I study may understate the magnitude of the problem relative to other regions.

Indeed, descriptive evidence from other regions suggests that transmission congestion and associated curtailments are large problems. Data from Millstein, O'Shaughnessy and Wiser (2024) show wide spatial variation in wholesale electricity prices across the United States from 2016 through 2023. This is true across several metrics: the average hourly price, the frequency of negative-price occurrences, and the average price across the 100 highest-price hours. And Davis, Hausman and Rose (2023) and Department of Energy (2023*a*) show that the Midwest is not alone in experiencing growing renewables curtailment. As Millstein et al. (2021) note, curtailments are not in of themselves problematic, if they reflect high renewables penetration as opposed to transmission congestion. However, curtailments to date are widely seen as resulting from congestion (Energy Information Administration, 2023*b*; Wilson, 2023; Potomac Economics, 2024).

Future research could expand on my results in several ways. It could be useful to look at emissions outcomes across my 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 effect on fossil plant retirements and on new wind entry.[53] A dynamic model, along the lines of Linn and McCormack (2019), Gonzales, Ito and Reguant (2023), 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 my analysis by incorporating reliability impacts. The existing transmission network to some extent reflects the fact that grid operators have historically prioritized reliability when planning transmission upgrades. Nonetheless,

[53] 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.

some have argued that winter storms Uri and Elliott – in 2021 and 2022 – have demonstrated the need for greater interregional transmission lines to storm-proof the grid (Goggin and Schneider, 2022; Goggin and Zimmerman, 2023*a*). It is possible that reliability benefits are as large, or even larger than, the allocative efficiency benefits that I quantify.

Finally, additional research on the cases in which incumbent utilities have tried to block 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 in economics 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). For the case of transmission planning, research largely comes from the law literature. Specific tactics a utility might use to favor its interests are detailed most extensively in Peskoe (2023) but also in Welton (2021); Kovvali and Macey (2023); Ansolabehere et al. (2024*a*) and Ansolabehere et al. (2024*b*). Some of the tactics named include: leveraging Regional Transmission Organization voting rules to disadvantage new transmission development; preempting interregional lines with a utility's own localized transmission or generation projects; or funding grassroots opposition groups. The literature has examined numerous case studies; broader quantitative evidence is still lacking. That may be difficult to obtain: the activities of stakeholders are hard to observe. Indeed, Macey, Welton and Wiseman (2024) argue that current governance structures "allow large, entrenched actors to implement their agendas across institutions in opaque and unaccountable ways" (p. 171).

Analysts have proposed a suite of reforms to transmission planning, permitting, and siting.[54] Perhaps most ambitious are the proposals for centralized federal authority over transmission planning and operations. Smaller-scale reforms include changes to FERC's processes, and updated guidelines for regional organizations. Alternatives to building new transmission lines have also been proposed: relying on batteries and other forms of storage instead; building renewables at such a large scale that major new interregional transmission is not needed; or upgrading existing corridors rather than building new lines. And in addition to calls for physical build-out of the transmission network, there has been a push for the removal of institutional constraints across markets. What the results of this paper suggest is that anticipating the incentives of incumbent utilities in *any* new or modified transmission process will be important, irrespective of which policy reforms ultimately move forward. That is, reforms that do not address underlying governance issues – arising from utility incentives that are not matched to those of society as a whole – may be less likely to deliver

[54]Examples include Welton (2021); Klass et al. (2022); Kovvali and Macey (2023); Peskoe (2023); Energy and Environmental Economics Inc (2024); Macey, Welton and Wiseman (2024); Simeone and Rose (2024); and Welton (2024).

the end results that policymakers desire.

My results relate to 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 is 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 Online Appendix

Appendix A1 shows additional tables and figures, referenced in the main text. Appendix A2 provides a detailed discussion of model fit. Appendix A3 discusses the modeling of plant outages. Appendix A4 investigates alternative market integration counterfactuals, connecting only two regions at a time.

Table A1: Most Transmission Upgrades Are Single-State

State	Count	State	Count	State	Count
AR	88	IA	236	IL	272
IN	249	KS	134	KY	14
LA	169	MI	375	MN	178
MO	79	MS	77	MT	6
ND	70	NE	49	NM	92
OK	155	SD	37	TX	158
WI	257	Multiple	70		

Note: This table shows the count of in-service or completed transmission upgrades reported by MISO and SPP over 2016-2022. MISO source: MISO Transmission Expansion Plan (MTEP) In Service Project List. SPP source: Quarterly Project Tracking Reports, 2016-Q1 2023.

Table A2: Location of Cross-State Upgrades

Location	Count	Location	Count	Location	Count
AR; OK	1	IA; IL	2	IA; IL; MN	15
IA; MN	11	IA; MO	1	IL; IN	1
IL; MO	6	IN; KY	1	LA; MS	2
MB; MN	1	MI; OH	1	MI; WI	14
MN; ND	1	MN; ND; SD	2	MN; WI	3
ND; SD	3	NM; TX	1	TX; AR	1
TX; NM	1	TX; OK	2		

Note: This table shows the count of multi-state in-service or completed transmission upgrades reported by MISO and SPP over 2016-2022. MISO source: MISO Transmission Expansion Plan (MTEP) In Service Project List. SPP source: Quarterly Project Tracking Reports, 2016-Q1 2023.

Table A3: Upgrade Types

Type	Count
Panel A: MISO	
Age and Condition	461
Baseline Reliability Project (BRP)	383
Generator Interconnection Project (GIP)	206
Load Growth	144
Local Needs	85
Local Reliability	820
Market Efficiency Project (MEP)	3
Market Participant Funded Project (MPFP)	1
Multi-Value Project (MVP)	13
Transmission Delivery Service Project (TDSP)	2
Targeted Market Efficiency Project (TMEP)	7
Panel B: SPP	
Balanced Portfolio	3
Economic	24
Generation Interconnection	148
Generator Interconnection	2
High Priority	80
Regional Reliability	414
Regional Reliability - Non OATT	1
Sponsored Upgrade	8
TO - Sponsored	8
Transmission Service	24
Zonal Reliability	8

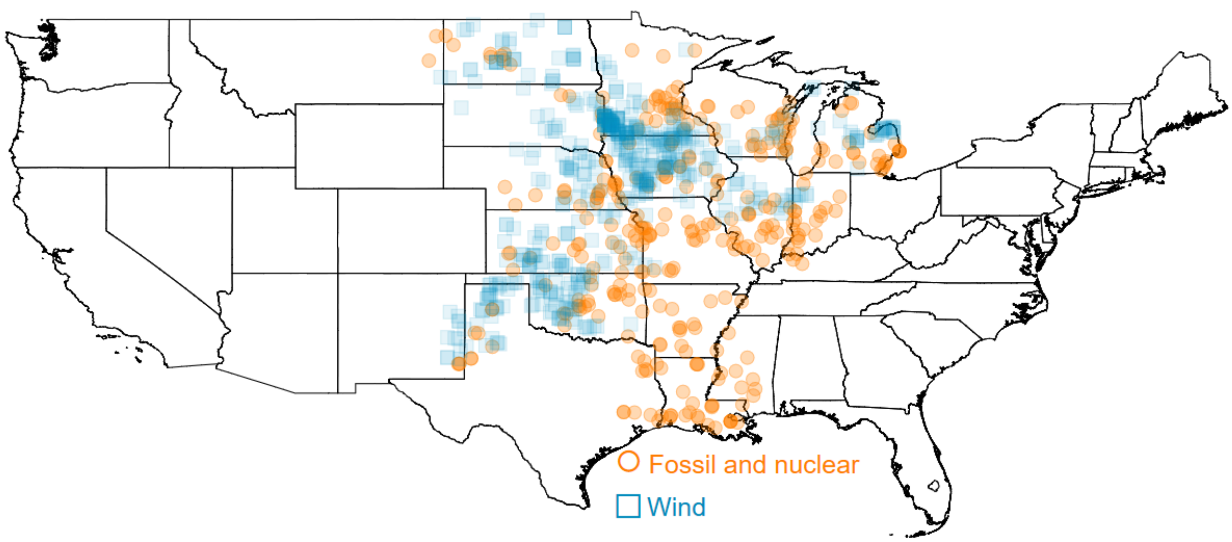
Note: This table shows the count of in-service or completed transmission upgrades, by type, reported by MISO and SPP over 2016-2022. MISO source: MISO Transmission Expansion Plan (MTEP) In Service Project List. SPP source: Quarterly Project Tracking Reports, 2016-Q1 2023.

Table A4: 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
Fuel price:					
Coal, $/MMBtu	11,381,964	2.35	0.63	1.24	13.9
Coke, $/MMBtu	245,304	2.82	1.33	1.22	6.82
Natural gas, $/MMBtu	39,254,482	4.16	1.65	-0.35	29.2
Oil, $/MMBtu	2,457,428	17.7	5.07	-6.89	35.2
Curtailments time series:					
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 gen., in MISO, MWh	61,325	0.072	0.100	0	4.13
Wind curtailment divided by wind gen., in SPP, MWh	61,257	0.028	0.054	0	0.71
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	61,287	30482.4	5628.1	19846.0	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	61,270	225428.6	40921.2	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

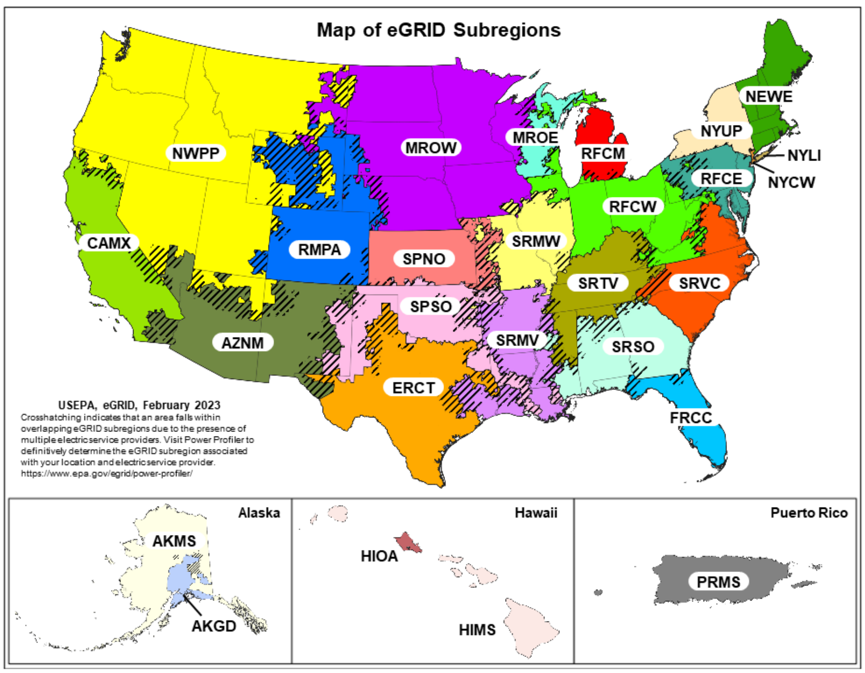
Note: This table provides summary statistics for my main estimation sample, at the generator by hour level. The sample is an unbalanced panel covering the period 2016-2022, with 993 generating units at 367 power plants. This represents all CEMS-reporting power plants (generally, fossil-fuel fired units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

Figure A1: Plant Locations by Fuel Type



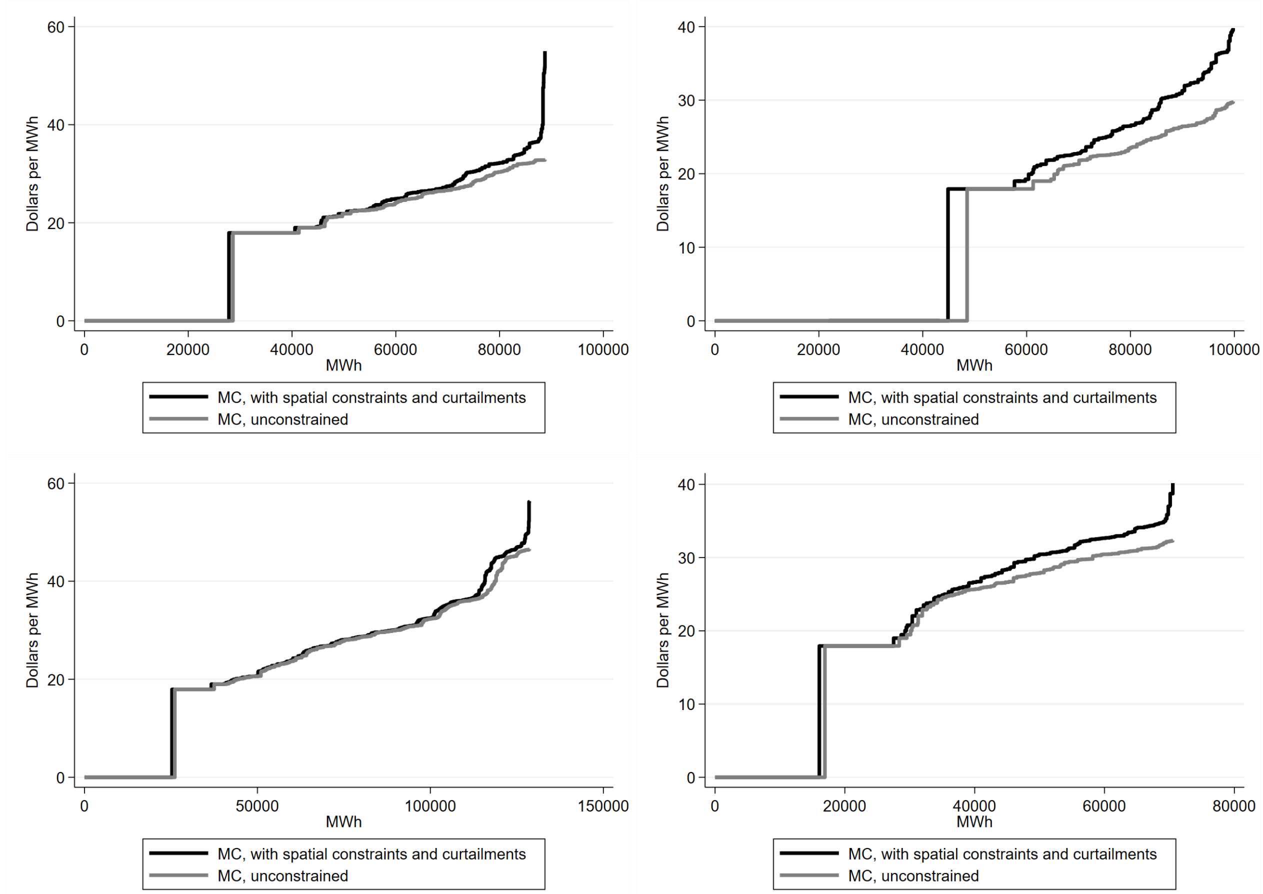
Note: This map shows the location of plants in the sample, by fuel type.

Figure A2: NERC Subregion Boundaries



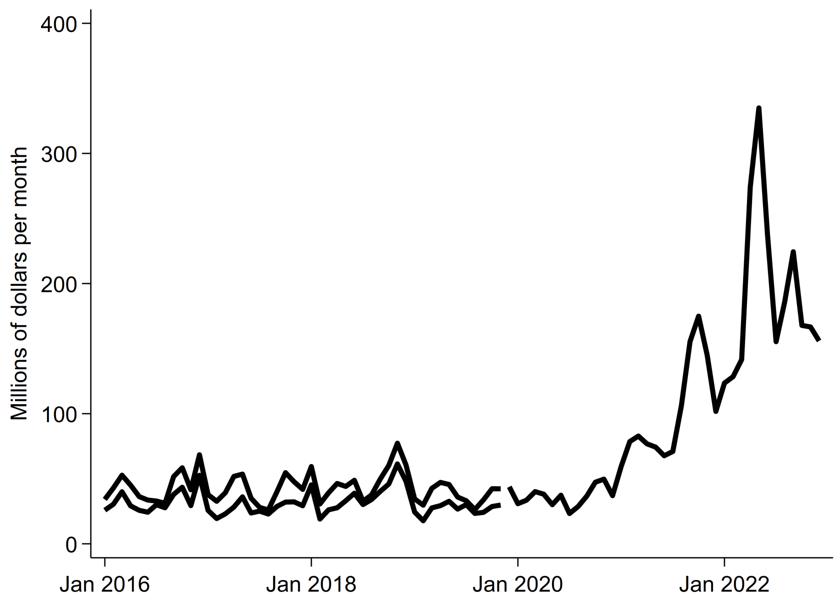
Note: This map shows NERC subregion boundaries as reported in eGRID. I interact these with a MISO versus SPP indicator to create the subregions that I implement in my main regionally-constrained counterfactual. Most of the subregions lie within only MISO or only SPP, but note that MROW has a number of plants in each of the ISOs. Map is from `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 A3: Additional Examples: Marginal Costs of Dispatched Generators



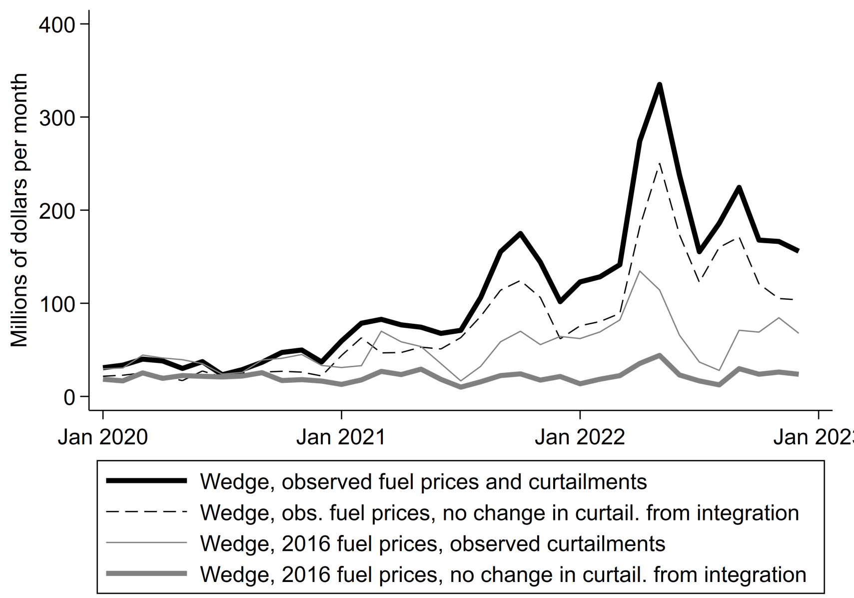
Note: This figure is constructed like Figure 1 in the main text, but showing alternative date-hour combinations. Note the scales of both axes vary across the four panels. The upper left panel shows an hour typical of the whole sample (2016 to 2022). The upper right panel shows an hour with particularly high curtailments (approximately two standard deviations above the sample mean for 2016-2022). The bottom left 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 A4: Additional Generation Costs From Spatial Constraints: 2016-2022



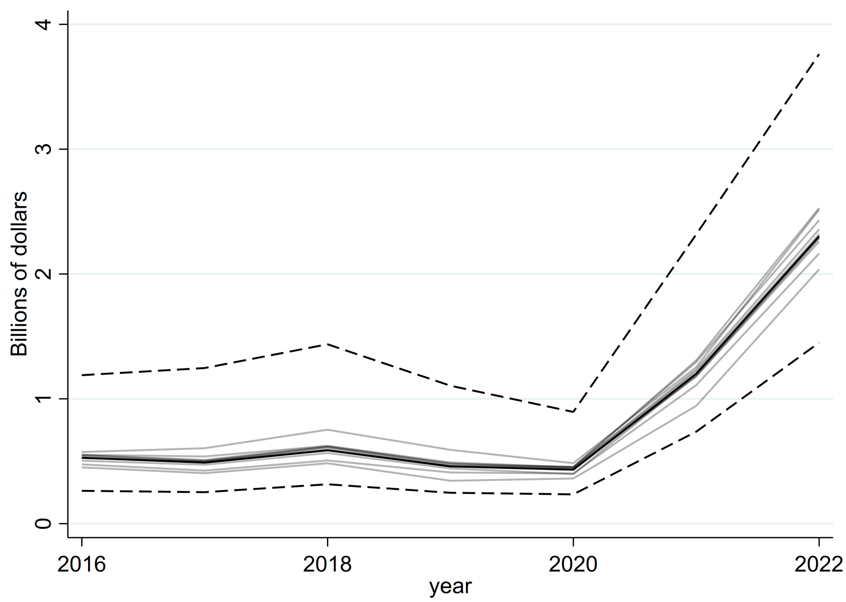
Note: This figure matches Figure 2 in the main text, but going back farther in time. For 2016 to 2019, curtailments are not observed. The two black lines for this time period show rough bounds. Specifically, the lower line assumes no wind was curtailed. In contrast, the upper line assumes the same quantity 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 A5: Holding Fuel Prices And/Or Curtailments Constant: Additional Generation Costs From Spatial Constraints



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

Figure A6: Robustness: Additional Generation Costs From Spatial Constraints



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 spatial constraints are measured at the ReEDS-zone level; the lower dashed line assumes spatial 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 A5: Alternative Specifications: Allocative Inefficiencies Increase as Wind Curtailments Increase

Panel A:	(1)	(2)	(3)	(4)	(5)	(6)
Demand	0.68***	0.26***	0.65***	0.66***	0.67***	
	(0.086)	(0.057)	(0.080)	(0.21)	(0.086)	
Load net of nuclear gen						0.67***
						(0.085)
Natural gas price	20726.7***	34191.4***	20357.4***	34032.3***	27584.3***	20767.8***
	(2894.8)	(3457.4)	(2753.2)	(3838.2)	(2983.9)	(2922.6)
Oil price	216.4	342.8	222.9	204.3	189.7	213.4
	(254.6)	(208.7)	(255.7)	(228.0)	(253.0)	(253.6)
Wind generation + curtailments	4.19***	4.81***	4.23***	4.53***	4.20***	4.19***
	(0.22)	(0.22)	(0.22)	(0.25)	(0.23)	(0.22)
Observations	61,266	61,266	61,266	61,266	60,594	61,266
R^2	0.79	0.71	0.79	0.73	0.80	0.79

Panel B:	(1)	(2)	(3)	(4)	(5)	(6)
Demand	0.69***	0.47***	0.74***	0.83***	0.67***	
	(0.079)	(0.048)	(0.073)	(0.18)	(0.078)	
Load net of nuclear gen						0.69***
						(0.079)
Natural gas price	20643.9***	31975.2***	20614.4***	30971.9***	29536.4***	20680.6***
	(3495.6)	(3236.4)	(3425.0)	(3482.8)	(2546.8)	(3524.1)
Oil price	380.6*	237.3	380.8*	62.5	347.6*	377.8*
	(207.8)	(194.3)	(208.0)	(205.8)	(203.9)	(205.4)
Wind generation	1.09***	1.40***	1.10***	0.83***	1.07***	1.09***
	(0.12)	(0.13)	(0.12)	(0.14)	(0.12)	(0.12)
Wind curtailments	35.9***	39.0***	35.9***	39.7***	36.1***	36.0***
	(1.16)	(1.49)	(1.16)	(1.48)	(1.17)	(1.16)
Observations	61,266	61,266	61,266	61,266	60,594	61,266
R^2	0.86	0.80	0.86	0.82	0.86	0.86

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 A6: Heterogeneity by Level of Load: Allocative Inefficiencies Increase as Wind Curtailments Increase

	Load $\in$ (70400, 94258]	Load $\in$ (94258, 103334]	Load $\in$ (103334, 114929]	Load $\in$ (114929, 170985)
Panel A				
Demand	0.24	0.11	1.10***	0.99***
	(0.18)	(0.22)	(0.29)	(0.17)
Natural gas price	21032.2***	27460.1***	28813.3***	17030.9***
	(4197.0)	(3257.6)	(3735.3)	(1588.5)
Oil price	-165.5	172.9	357.5	1069.2
	(175.4)	(244.9)	(455.3)	(793.4)
Wind generation + curtailments	4.44***	4.14***	4.26***	3.62***
	(0.22)	(0.24)	(0.28)	(0.39)
Observations	15,311	15,319	15,318	15,317
R^2	0.88	0.85	0.80	0.72
Panel B				
Demand	0.88***	0.67***	1.21***	1.05***
	(0.15)	(0.15)	(0.21)	(0.15)
Natural gas price	23921.7***	28944.8***	30759.5***	17074.0***
	(2726.8)	(2663.2)	(2986.0)	(2293.1)
Oil price	180.2	119.2	233.0	1140.1*
	(137.9)	(203.9)	(322.6)	(633.4)
Wind generation	0.86***	0.82***	0.66***	0.23
	(0.097)	(0.11)	(0.15)	(0.24)
Wind curtailments	29.1***	37.4***	44.4***	61.6***
	(0.59)	(1.24)	(2.08)	(5.05)
Observations	15,311	15,319	15,318	15,317
R^2	0.95	0.92	0.89	0.79

Note: Panel A of this table matches Column 1 of Table 2 in the main text, but divides the panel into four subsamples based on the level of system-wide load. Panel B similarly matches Column 2.

Table A7: Heterogeneity by Level of Wind: Allocative Inefficiencies Increase as Wind Curtailments Increase

	Wind $\in$ $(516, 9715]$	Wind $\in$ $(9715, 15249]$	Wind $\in$ $(15249, 22299]$	Wind $\in$ $(22299, 50654)$
Panel A				
Demand	0.87***	0.53***	0.41***	0.74***
	(0.074)	(0.087)	(0.088)	(0.23)
Natural gas price	14138.2***	27446.1***	29106.2***	40730.4***
	(764.9)	(2748.8)	(3295.2)	(3541.0)
Oil price	-37.5	255.2	409.3	550.2
	(263.6)	(185.5)	(268.3)	(442.3)
Wind generation + curtailments	-0.14	0.79***	3.32***	8.54***
	(0.27)	(0.24)	(0.26)	(0.36)
Observations	15,320	15,313	15,316	15,317
R^2	0.58	0.69	0.76	0.87
Panel B				
Demand	0.86***	0.52***	0.42***	1.03***
	(0.073)	(0.087)	(0.088)	(0.23)
Natural gas price	14079.0***	27532.7***	29587.4***	41157.3***
	(743.1)	(2643.7)	(3098.9)	(2892.9)
Oil price	-31.8	337.2*	573.2***	650.7*
	(262.6)	(175.0)	(203.6)	(333.4)
Wind generation	-0.35	0.23	1.34***	1.85***
	(0.27)	(0.24)	(0.20)	(0.35)
Wind curtailments	25.6***	35.2***	39.5***	31.3***
	(4.44)	(2.38)	(1.89)	(1.07)
Observations	15,320	15,313	15,316	15,317
R^2	0.58	0.70	0.81	0.91

Note: Panel A of this table matches Column 1 of Table 2 in the main text, but divides the panel into four subsamples based on the level of system-wide wind potential. Panel B similarly matches Column 2.

Table A8: Heterogeneity by Season, Day, or Hour: Allocative Inefficiencies Increase as Wind Curtailments Increase

	Winter	Spring	Summer	Fall	Weekend	Weekday	Offpeak	Peak
Panel A								
Demand	1.19***	0.99***	0.57**	0.87***	0.80***	0.75***	0.18*	1.01***
	(0.22)	(0.27)	(0.26)	(0.22)	(0.14)	(0.097)	(0.11)	(0.12)
Natural gas price	18830.5***	43400.0***	24423.3***	16188.8***	17532.7***	20917.2***	20763.8***	20877.8***
	(2799.2)	(8603.3)	(6636.8)	(5482.1)	(5740.9)	(3422.5)	(3613.7)	(2303.2)
Oil price	812.2	-361.7*	875.8	229.0	-246.4	361.2	184.9	252.8
	(646.8)	(206.5)	(948.0)	(693.3)	(435.6)	(294.3)	(257.6)	(294.7)
Wind gen. + curtail.	3.73***	4.72***	3.49***	4.69***	4.16***	4.19***	4.54***	3.77***
	(0.33)	(0.45)	(0.55)	(0.43)	(0.26)	(0.24)	(0.22)	(0.25)
Observations	15,156	15,424	15,450	15,236	17,490	43,776	33,161	28,105
R^2	0.73	0.88	0.75	0.75	0.83	0.79	0.84	0.75
Panel B								
Demand	1.35***	1.30***	0.64***	1.11***	0.79***	0.69***	0.41***	1.13***
	(0.18)	(0.27)	(0.19)	(0.20)	(0.13)	(0.086)	(0.10)	(0.11)
Natural gas price	17820.1***	38772.6***	33829.5***	22020.8***	22800.0***	20284.1***	20640.8***	20394.8***
	(2818.3)	(6300.1)	(5698.6)	(4978.6)	(4783.3)	(3646.8)	(4343.0)	(2574.2)
Oil price	415.8	-68.6	1648.9***	515.1	159.8	438.3**	391.7*	375.3
	(424.6)	(182.6)	(618.9)	(567.7)	(388.6)	(215.9)	(213.0)	(249.1)
Wind generation	0.94***	1.29***	0.40*	0.87***	1.17***	1.05***	1.31***	0.52***
	(0.19)	(0.21)	(0.23)	(0.27)	(0.17)	(0.13)	(0.12)	(0.13)
Wind curtailments	34.3***	32.1***	62.6***	38.3***	33.6***	36.9***	32.8***	43.7***
	(1.25)	(1.67)	(5.37)	(2.02)	(1.54)	(1.26)	(0.91)	(1.97)
Observations	15,156	15,424	15,450	15,236	17,490	43,776	33,161	28,105
R^2	0.85	0.93	0.82	0.83	0.88	0.86	0.90	0.83

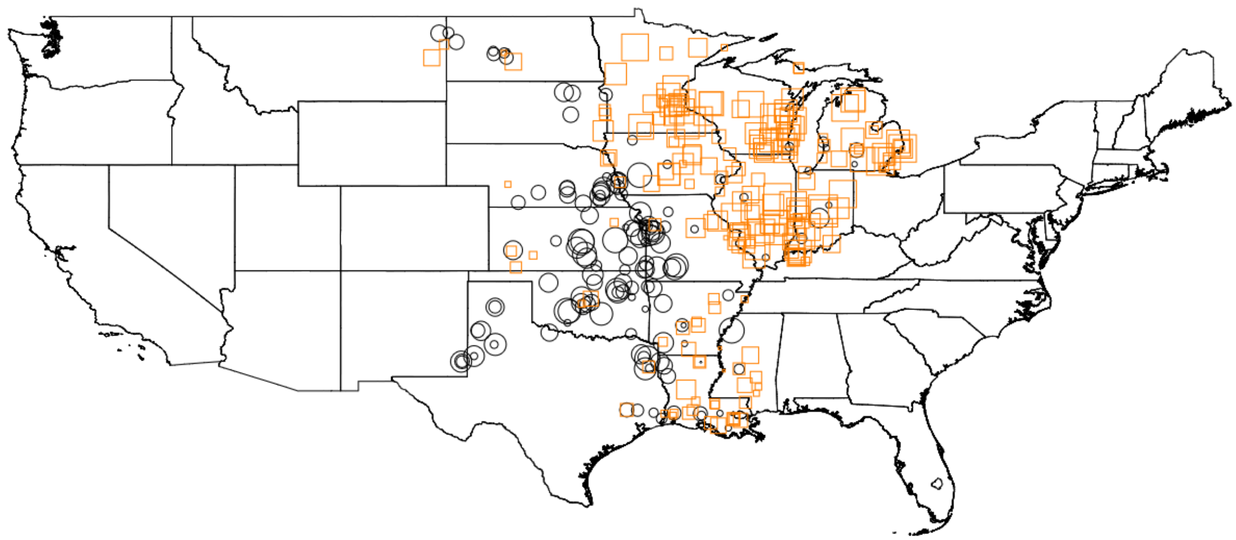
Note: Panel A of this table matches Column 1 of Table 2 in the main text, but divides the sample into four seasons, then two day types, then two hour of day types. Panel B similarly matches Column 2.

Table A9: 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 A7: 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 A10: Alternative Specifications: Incentives to Block Market Integration Increase as Renewables Enter

	(1)	(2)	(3)	(4)	(5)
Potential wind generation, GWh	-3085***	-3026***	-3202***	-3065***	-3172***
	(284)	(247)	(278)	(287)	(285)
Observations	61,284	61,284	61,284	60,612	61,284
R^2	0.18	0.18	0.13	0.19	0.18

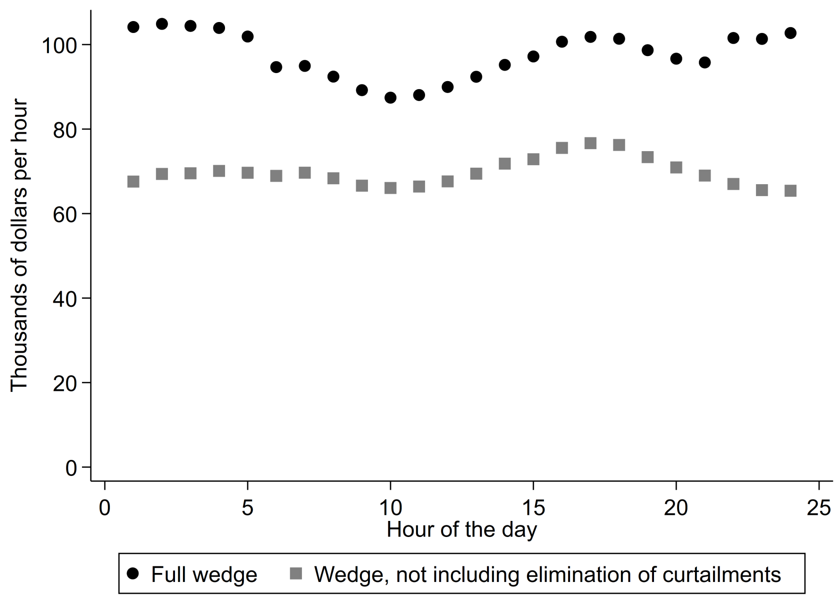
Note: This table matches Column 3 of Table 3 from the main text, but for various alternative specifications. Column 1 recreates Column 3 of Table 3. Column 2 drops the weather controls. Column 3 drops the time effects. Column 4 drops the period of Winter Storm Uri. Column 5 includes more saturated time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

Table A11: Additional Results: Incentives to Block Market Integration Increase as Renewables Enter

	(1) Net revenues, spatially-constrained	(2) Net revenues, integrated market	(3) Change in net revenues from integration
Panel A: Net revenues, conventional gen.			
Potential wind generation, GWh	-1331***	-4415***	-3085***
	(241)	(283)	(284)
Observations	61,284	61,284	61,284
R^2	0.53	0.80	0.18
Panel B: Net revenues, wind gen.			
Potential wind generation, GWh	20671***	28868***	8196***
	(413)	(495)	(406)
Observations	61,284	61,284	61,284
R^2	0.78	0.91	0.38

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 potential wind generation across MISO and SPP, summing across actual wind generation and curtailed wind generation, in GWh. Standard errors are clustered by sample week.

Figure A8: Allocative Inefficiencies Occur In All Hours of the Day

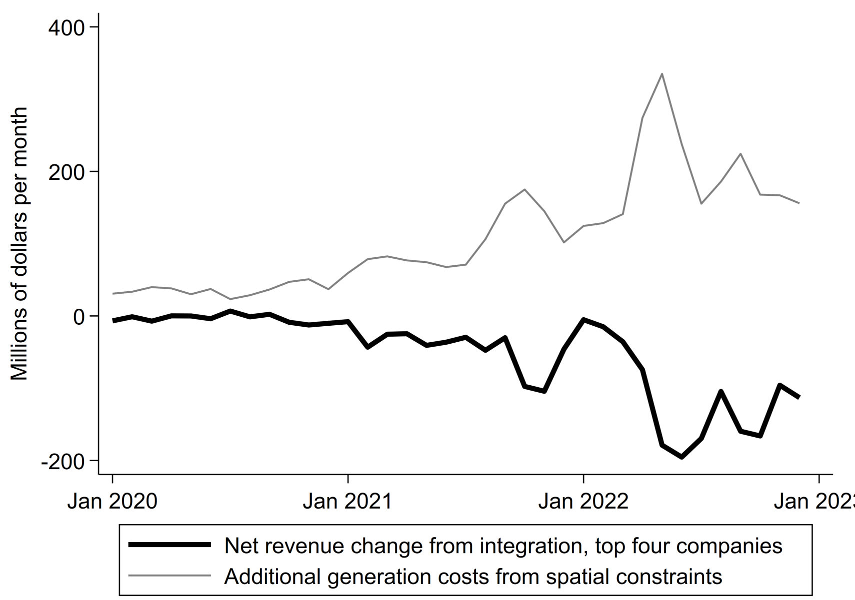


Note: This figure shows the average hourly allocative inefficiency across hours of the day. Allocative inefficiencies rise at night, but that is a function of higher curtailments rather than inefficiencies within fossil unit dispatch per se.

Figure A9: Robustess Check: Alternative Subregion Boundaries

Note: This map shows subregion boundaries from the ReEDS model, which I use to define regional constraints in a robustness check. As with the NERC subregions, I interact these with a MISO versus SPP indicator to define regional constraints (in my sample, most but not all zones lie within just one ISO).

Figure A10: Losses for Top Four Firms Versus Society-Wide Allocative Inefficiencies



Note: This figure matches Figure 2 in the main text, but adds a line for the net revenue change at the top four firms reported on in the text – specifically, the four firms that stood to lose the most from integration under 2022 conditions, not accounting for subsidiary ownership.

Table A12: SPP Prices Respond More to Local Demand Shocks

	North SPP	South SPP
Panel A: SPP versus MISO demand shocks		
SPP load, GWh	1.22***	2.12***
	(0.19)	(0.24)
MISO load, GWh	0.41***	0.30*
	(0.12)	(0.16)
Observations	59,835	59,835
R^2	0.16	0.22
Panel B: North versus Central versus South demand shocks		
North SPP load, GWh	6.92***	0.02
	(1.04)	(1.11)
Central SPP load, GWh	0.69	1.49
	(0.80)	(1.01)
South SPP load, GWh	-0.13	3.08***
	(0.42)	(0.50)
MISO load, GWh	0.24**	0.39**
	(0.11)	(0.16)
Observations	59,835	59,835
R^2	0.16	0.22

Note: This table shows results from four separate horse race regressions. The dependent variable is a wholesale price, in dollars per MWh. The unit of observation is an hour. Panel A examines whether the price adjusts more in response to SPP or to MISO demand shocks; Panel B disaggregates SPP demand into North, Central, and South demand shocks. All regressions control for Eastern Interconnection demand, fuel prices, weather, and time effects.

Table A13: MISO Prices Respond More to Local Demand Shocks

	Arkansas	Illinois	Indiana	Louisiana	Michigan	Minnesota	Mississippi	Texas
Panel A: SPP versus MISO demand shocks								
SPP load, GWh	0.36***	-0.52***	-0.81***	0.34*	-0.92***	-0.20	0.48**	0.49*
	(0.11)	(0.15)	(0.19)	(0.20)	(0.18)	(0.16)	(0.20)	(0.25)
MISO load, GWh	0.88***	1.25***	1.36***	1.17***	1.46***	1.17***	1.09***	0.93***
	(0.17)	(0.14)	(0.19)	(0.19)	(0.18)	(0.12)	(0.23)	(0.24)
Observations	60,598	60,598	60,598	60,598	60,598	60,598	43,822	60,598
R^2	0.28	0.30	0.31	0.17	0.30	0.23	0.26	0.08
Panel B: North versus Central versus South demand shocks								
North MISO load, GWh	-0.78	-1.16***	-1.52***	-0.20	-1.48***	3.47***	-0.51	0.73
	(0.50)	(0.39)	(0.52)	(0.82)	(0.44)	(0.48)	(0.77)	(1.17)
Central MISO load, GWh	0.84***	2.32***	2.36***	0.58*	2.81***	0.53***	0.78***	0.98**
	(0.22)	(0.21)	(0.32)	(0.30)	(0.28)	(0.17)	(0.29)	(0.43)
South MISO load, GWh	3.07***	0.79*	1.71***	4.75***	0.77*	0.38	4.03***	1.00
	(0.76)	(0.47)	(0.63)	(0.71)	(0.44)	(0.32)	(0.85)	(3.30)
SPP load, GWh	0.07	-0.18	-0.59***	-0.27	-0.48**	-0.27	0.02	0.49
	(0.15)	(0.17)	(0.22)	(0.24)	(0.18)	(0.17)	(0.24)	(0.74)
Observations	60,598	60,598	60,598	60,598	60,598	60,598	43,822	60,598
R^2	0.29	0.31	0.31	0.18	0.30	0.23	0.28	0.08

Note: This table matches Table A12 but for MISO prices.

A2 Model Fit

This appendix compares various outcomes from the counterfactuals to observed outcomes, to assess model performance. I examine generation outcomes, prices, and geographic price dispersion (a measure of congestion).

A2.1 Observed versus modeled generation quantities

First, I describe the extent to which modeled generation data matches observed generation data. I focus on my main regionally-constrained counterfactual, which is intended to mimic market and grid conditions in the real world. This gives reassurance that the main modeling assumptions are reasonable. I next show that the similarities between observed and modeled generation hold up under the various alternative modeling assumptions explored in my robustness checks. Throughout I consider the first and second moments of each variable as well as the correlation between observed and modeled variables.

The means of the observed and the modeled regionally-constrained quantity are the same, by construction (Table A14). The modeled unconstrained quantity is lower, by construction – recall that wind has been assumed to provide the remaining generation. The modeled standard deviation is of a comparable magnitude to the observed standard deviation in both the constrained and unconstrained counterfactuals, although the modeled standard deviation is a bit (8%) higher. In the model, units are frequently at the corner solution (fully off or fully dispatched), whereas in the real world some units operate at, e.g., 90% of their capacity while they leave 10% for reserves provision (for a model of this, see Buchsbaum et al., 2024).[55]

Table A14: Observed Versus Modeled Generation, First and Second Moments

	Count	Mean	SD
Observed generation	53,339,178	71.06	149.34
Modeled constrained generation	53,339,178	71.06	160.69
Modeled unconstrained generation	53,332,300	70.11	161.66

Note: This table summarizes observed versus modeled generation. Note that modeled unconstrained generation is missing in a small number of hours because curtailments data are missing.

The model also does a good job replicating other moments, as shown in Table A15. Most units are typically off; the system is built to have capacity sufficient to meet demand even on the hottest weekday afternoons.

[55] Buchsbaum, J., Hausman, C., Mathieu, J. L., and Peng, J. “Spillovers from ancillary services towholesale energy markets.” *RAND Journal of Economics*, Vol 55, No. 1, (2024), pp 87-111.

Table A15: Observed Versus Modeled Generation, Additional Statistics

	25th	Median	75th
Observed generation	0.00	0.00	49.96
Modeled constrained generation	0.00	0.00	0.00
Modeled unconstrained generation	0.00	0.00	0.00

Note: Like Table A14, this table summarizes observed versus modeled generation.

If we look at 6 pm weekday hours (when demand is typically higher) and at low marginal cost units (which are likely to be dispatched), the moments again match well (Table A16). Many units are still off, in part because of stochastic outages. More importantly, these moments of observed generation closely match the moments of modeled constrained generation. Overall, the various moments of modeled and observed quantities match well; some (but not all) by construction.

Table A16: Observed Versus Modeled Generation, Additional Statistics, 6 pm Weekday Hours at Low Marginal Cost Units

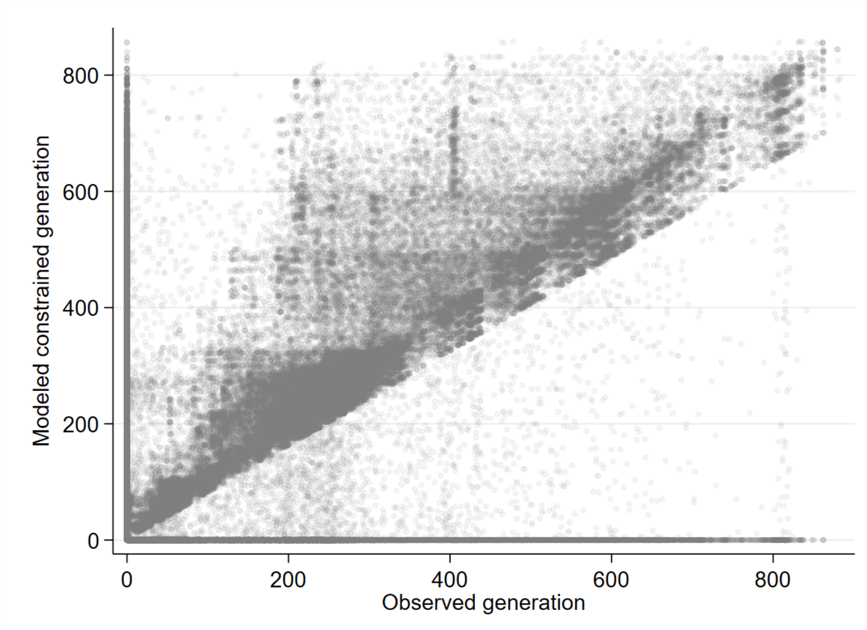
	25th	Median	75th
Observed generation	0.00	210.73	402.06
Modeled constrained generation	0.00	244.19	462.39
Modeled unconstrained generation	62.85	254.58	472.29

Note: This table mimics A15, but limits the sample to 6 pm weekday hours (when demand is typically higher) at low marginal cost ($\leq$ \$30/MWh) units (which are likely to be dispatched).

Correlations between observed and modeled generation are also high. The correlation at the hour-by-unit level (n=53 million) is 0.68; the correlation is, as expected, slightly lower in the unconstrained counterfactual (0.66). It is not surprising that neither correlation is not 1.0 – indeed, it is surprising it they are this high – since outages are stochastic. A scatterplot (Figure A11) gives insight into the reasons they are not equal to 1. Unplanned outages are stochastic and therefore will lead to a mismatch between observed and modeled quantities – this explains the mass of units at zero generation of one variable but not the other, i.e. along both the horizontal and vertical axes.

Many of the other off-diagonal points are explained by two features of the model. (1) Recall that to keep from introducing too much convexity in the supply curve, I have modeled planned outages as capacity derates, with varying percentages derated across months, to match ISO-reported data – this explains the modeled quantities that are just below total capacity at times when observed quantities are at maximum capacity. (2) The model has more corner solutions (units at zero or at maximum capacity, derated) than in the real world, as described above – this explains modeled quantities that are at total capacity (albeit derated) at times when observed quantities are below total capacity.

Figure A11: Observed Versus Modeled Generation, Hourly Correlation



Note: This figure shows observed versus modeled generation for a random subsample (1%) of hour-by-unit observations.

The correlation (between observed and modeled constrained generation) at the month-by-unit level, which smooths over the shocks from stochastic outages, is higher: 0.84. The year-by-unit correlation is 0.91; and the cross-sectional correlation at the unit level is 0.95. Thus the model accurately predicts which units tend to get dispatched and which do not.

Another useful correlation to examine is at the region by month by fuel and technology level: this asks, does the model do a good job of dispatching coal versus natural gas across space and across time. This correlation is 0.98.

Finally, I show that the hourly correlations are similar under the various robustness checks. That is, the correlation is not sensitive to the various modeling assumptions explored in the robustness checks section. The robustness check with the most different correlation is the one in which outages are modeled as derates for both planned and unplanned outages (r=0.73). This is not surprising; as described above, I model unplanned outages as stochastic to match the distribution of market outcomes, not the outcomes in a particular hour. The other robustness check that has a somewhat high correlation uses the ReEDS regional definitions; by construction, this will more closely match observed outcomes, but it comes with a higher risk of overstating the role of transmission constraints, as described in the main text.

Table A17: Observed Versus Modeled Generation, Correlation with Robustness Checks

Assumptions for modeling generation	Correlation with obs. gen.
Constrained counterfactual, main specification	0.68
Broad regional definition	0.68
ReEDS regional definition	0.71
Including CHP	0.68
Heat rate and capacity, sample-wide	0.67
Outages: derating planned and unplanned	0.73
Time-invariant national fuel cost markup	0.68
Alternative CT MC (low O&M)	0.67
Alternative CT MC (high O&M)	0.68
Constraining CT quantities	0.67
Constraining units if observed below minimum constraint	0.68
Including line losses	0.68
Predicting regionally aggregated quantity with demand, wind	0.65

Note: The primary counterfactual yields modeled generation quantities at the unit-by-hour level that have a correlation of 0.68 with observed generation. This table shows the correlation for alternative modeling assumptions.

Thus overall, when considering various moments of individual variables or when considering correlations across variables, the model does a good job of mimicking observed generation data.

A2.2 Observed versus modeled prices

I next compare observed and modeled prices, using data on hourly locational marginal prices (LMPs) from both MISO and SPP. I focus on hub-level prices, which are roughly equal to the geographic level at which my regionally-constrained prices are constructed. I assign each power plant to a MISO or SPP hub, based on the NERC subregion by ISO where the plant is located. For NERC subregions with multiple price hubs, I take an average price across the hubs, weighted by the number of plants in the state of that hub.

I first report (Table A18) the moments of observed and modeled prices. For this calculation, I weight by observed quantities, as that is more relevant for the revenue calculations (as one extreme example: the price a unit receives is irrelevant if the unit is not generating).

Note the observation count is lower than in the summary tables for generation outcomes, as no weight has been applied to zero-generation observations. The observation count is somewhat different across rows in Panel A: observed prices are missing from the ISO data in some hours (in which I am still able to model prices), and there are different numbers of

Table A18: Observed Versus Modeled Prices

	Count	Mean	SD	25th	Median	75th
Panel A: All observations						
Observed price	16,415,804	39.99	60.27	24.08	29.89	41.91
Modeled constrained price	16,483,079	39.42	33.23	28.58	32.91	41.17
Modeled unconstrained price	16,481,673	37.14	14.02	29.59	32.76	39.19
Panel B: Observations where all three prices are observed:						
Observed price	16,414,450	39.99	60.27	24.08	29.89	41.91
Modeled constrained price	16,414,450	39.38	33.11	28.58	32.90	41.12
Modeled unconstrained price	16,414,450	37.11	14.00	29.58	32.73	39.14

Note: This table reports various moments of observed and modeled prices, weighted by observed generation. Note the observation count is lower than in the summary tables for generation outcomes, as no weight has been applied to zero-generation observations. The observation count is somewhat different across rows: observed prices are missing from the ISO data in some hours (in which I am still able to model prices), and prices are not modeled in the unconstrained counterfactuals if curtailments data are missing. Panel B limits the sample to hours when all three prices are available.

zero-generation observations in the constrained and unconstrained counterfactuals.[56] All the moments are similar if the table is restricted to hours where all three are observed (Panel B).

The moments are quite close: the modeled constrained price is within 2% of the observed price. This is strikingly close, given that I have not used LMP data in my model in any way – by making a few assumptions about marginal cost and about market-clearing, I can replicate the observed level of prices very closely.

As expected, the modeled constrained price is closer to the observed price than is the unconstrained price, which is too low. The standard deviation is also much closer in the constrained counterfactual than in the unconstrained counterfactual. This is consistent with spatial constraints binding in the real world and leading to price dispersion across space (more on this point, below).

The price correlations are as follows. As with quantity correlations, the hour-to-hour correlation will be lowered by outages. Again, I want to get the impact of stochastic outages correct on average, but I cannot match the specific hour-to-hour pattern of them. Moreover, one might expect the price correlation to be lower than the quantity correlation because of the convexity of the supply curve: changes in which combination of plants have an outage will push marginal cost up very steeply in some hours. The unit-by-hour correlation is 0.21. However, the correlation ignoring outliers (top and bottom 1%) in both series is

[56]Note the SPP data file is missing December of 2022; this accounts for most of the missing observed prices.

much higher: 0.55; consistent with steeply convex supply curves combined with stochastic outages leading to high prices in some hours. Recall that less important than matching the hour-to-hour correlation is getting plausible patterns across space and time. The unit-by-month correlation is 0.34, and the unit-by-month correlation after dropping hourly outliers is 0.74.[57] The unit-by-year correlation is 0.36; after dropping outliers it is 0.83. Finally, the cross-sectional correlation is 0.45, or 0.85 after dropping hourly outliers.

To ensure that the main results are not driven by these price outliers, Section 6 includes a robustness check that winsorizes unit-by-hour price hours at the top and bottom 1%. Results for Entergy's net revenues are similar in this robustness check. This is not the main specification because while it leads to a better correlation with observed prices, it does so at the expense of eliminating the high-price hours that electricity markets do experience when conditions are severely constrained. The goal of this paper is to model the typical distribution of prices across space and across time, which should incorporate things like plant outages leading to price spikes.

Another way to examine fit is to compare the geographic patterns in Figure 5 (the spatial patterns in changes in revenues) with geographic patterns in real-world prices. The ReWEP tool provided by LBNL allows for a rough comparison, as it shows annual average prices across both MISO and SPP for 2022 (Figure A12, below). It generally shows the lowest prices in places like Nebraska, Kansas, southwest Minnesota, and Northwest Iowa. These are places where I show that integration would bring gains to incumbent generators (Figure 5). A few differences are worth noting. First, the ReWEP tool is using locational prices at a fine scale, whereas my measures of transmission congestion are broader and interregional – for instance, I do not capture the differences within Kansas between the western and eastern portions of the state. My model also does not capture some of the high prices in parts of RFCW in 2022. Nonetheless, the broad geographic patterns are similar.

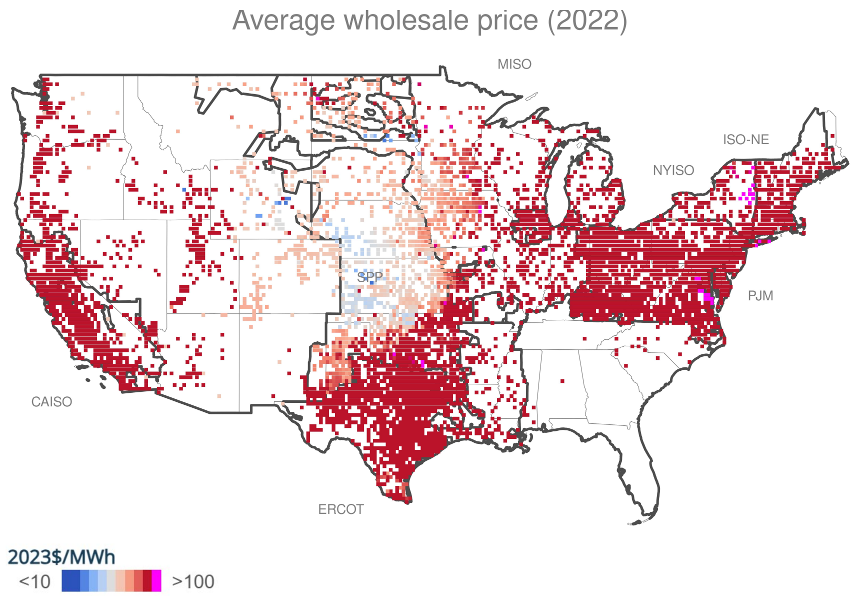
A2.3 Observed versus modeled geographic price dispersion

I finally consider a few additional outcomes beyond generation and prices. In addition to looking at the correlation of prices themselves, I can look at the geographic dispersion of prices.

Recall that I report that allocative inefficiencies have grown over the course of my sample (Figures 2 and A4). Here I show that the geographic dispersion in both observed and modeled prices is also growing over time. This provides reassurance that the overall conclusion that

[57]For all price correlations at aggregate levels (unit-by-month, unit-by-year, and cross-sectional), I weight by observed generation when aggregating. Weighted prices are more relevant for the revenue calculations (as one extreme example: the price a unit receives is irrelevant if the unit is not generating).

Figure A12: Average 2022 Locational Prices, from ReWEP



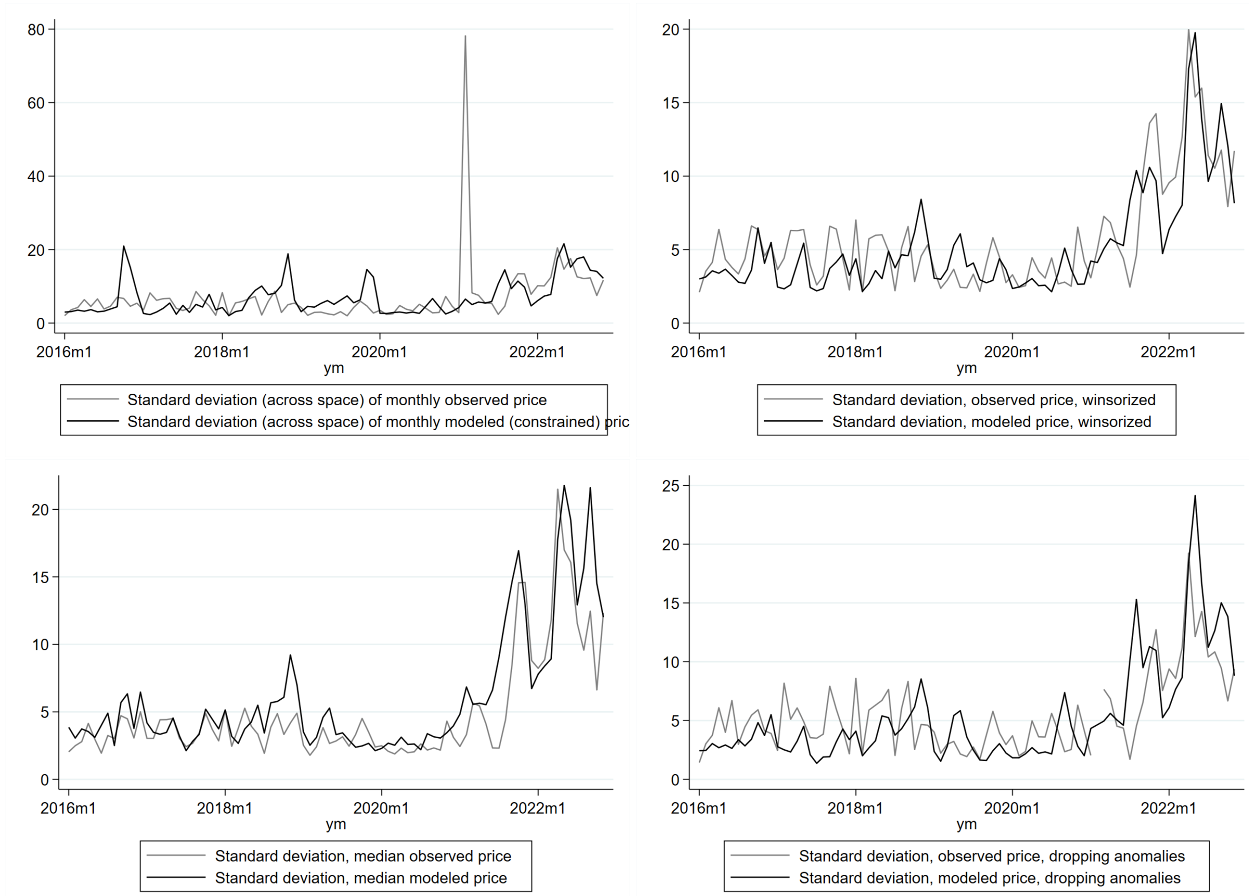
Note: This figure shows annual average prices for 2022, from Millstein, O'Shaughnessy and Wiser (2024).

spatial constraints have started to matter more in recent years is true in observable data, not just in modeled outcomes. Specifically, I calculate the mean monthly price for observed hub-level locational marginal prices and for modeled prices in the regionally-constrained counterfactual. I then calculate the standard deviation across geographic hubs for each of these two price variables. (Recall that the standard deviation of modeled prices in the unconstrained counterfactual is zero, as price is equalized across space by construction.) This gives an indication of how much prices are varying across space, and therefore how much spatial constraints matter. The first pass of this (top left panel of Figure A13) shows a few anomalies, explained below.

There are two differences in these two series in the upper left panel. Observed dispersion spikes during Winter Storm Uri (February 2021), which I have not modeled. As noted in the main text, there are reliability benefits of increased transmission, particularly during extreme events. And, I have some smaller price spikes early in my modeled price time series. These come from outlier hours that pull up the mean of one or two regional prices. The remaining three panels of Figure A13 show that this discrepancy does not show up in more typical hours, as measured by any of: the average of winsorized prices, the median monthly price, or the average of prices excepting two regions (MISO-MROE and SPP-MROW) and dropping the month of February, 2021 (Winter Storm Uri).

With any of these adjustments, observed price dispersion closely tracks the time path of

Figure A13: Price Dispersion, Observed versus Modeled



Note: This figure shows the standard deviation (across space) of monthly hub-level prices. The upper left panel uses observed and modeled prices. The upper right panel winsorizes both price series (1%) at the hourly level. The bottom left panel uses the median, not mean, across hours in a month. The bottom right panel drops two regions (MISO-MROE and SPP-MROW) and the month of February, 2021 (Winter Storm Uri).

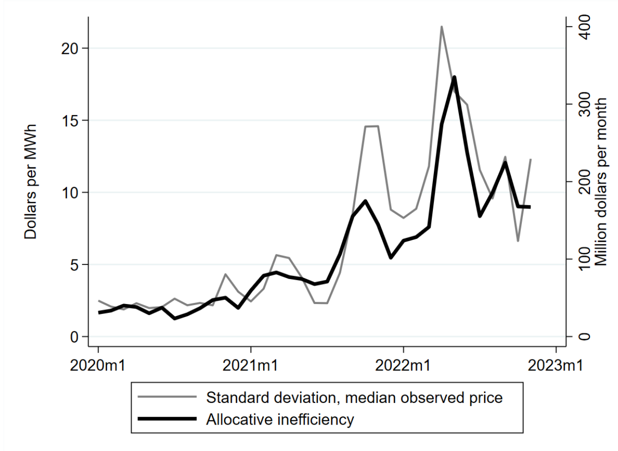
modeled price dispersion. One might worry that these anomalies drive the main results. So, a robustness check in the main paper show that the main results are similar with winsorized prices.

Moreover, the time path of observed price dispersion (Figure A14) closely matches the time path of the allocative inefficiencies reported in Figure 2. This provides reassurance that the allocative inefficiencies reported are indeed indicative of geographic constraints that lead to price separation across space.

A related question is: in hours with low dispersion across space in observed prices, how large is the modeled allocative inefficiency? Figure A13 is at the monthly level; this additional analysis has the advantage of looking at specific hours with low price dispersion.

When there is a large spread in prices across hubs, i.e. when the standard deviation of

Figure A14: Observed Price Dispersion versus Allocative Inefficiencies



Note: This figure matches the bottom left panel of Figure A13, but with allocative inefficiencies rather than modeled price dispersion.

prices across hubs is in the 5th quintile (around $43/MWh), the average allocative inefficiency is $184,000 per hour. In contrast, when the standard deviation of prices across hubs is in the 1st quintile (around $1.94/MWh), the average allocative inefficiency averages only $45,000 per hour. That is, going from the 5th to 1st quintile of price dispersion is correlated with a 76 percent lower allocative inefficiency. Some of this is because both price dispersion and the allocative inefficiency are correlated with natural gas prices (and so both are rising over time in my sample). So if we ignore 2022, for instance, going from the 5th to the 1st quintile of price dispersion is correlated with a 61 percent lower allocative inefficiency. Nonetheless the point holds that the modeled allocative inefficiencies are highly correlated with observed price dispersion.

Finally, just as the main text reports that allocative inefficiencies are correlated with demand, natural gas prices, and wind curtailments, so too is the price dispersion in LMPs (Table A19). The coefficients imply elasticities (at the mean values) of around: 3 for demand; 1 for natural gas prices; and 0.4 for wind (Column 1). The elasticity is larger for wind curtailments than for wind generation. Coefficients are similar when wind variables are instrumented for with a vector of state-level wind speeds, and wind speeds interacted with wind generation capacity.

A2.4 ISO-Reported Binding Constraints

I collect data from each ISO on the shadow value of real-time binding constraints. The unit of analysis is a constraint in an hour (the data are reported at 5-minute intervals, but I

Table A19: Price Dispersion Increases as Wind Curtailments Increase

	(1)	(2)	(3)	(4)
Demand	0.00038***	0.00038***	0.00037***	0.00037***
	(0.000019)	(0.000019)	(0.000018)	(0.000018)
Natural gas price	3.35***	3.34***	2.16**	2.19**
	(0.58)	(0.53)	(0.87)	(0.86)
Oil price	-0.030	-0.015	-0.011	-0.0049
	(0.032)	(0.030)	(0.030)	(0.030)
Wind generation + curtailments	0.00028***		0.00032***	
	(0.000019)		(0.000024)	
Wind generation		0.000058**		0.00022***
		(0.000023)		(0.000040)
Wind curtailments		0.0026***		0.0013***
		(0.00016)		(0.00033)
Observations	60,503	60,503	56,091	56,091
R^2	0.23	0.24	0.08	0.09
K-P F-stat			166	19

Note: This table matches Table 2 in the main paper, but with a measure of price dispersion as the dependent variable. This dispersion is calculated as the standard deviation (across space) in hourly hub-level locational marginal prices in SPP and MISO. This dispersion variable is winsorized at the upper and lower one percent.

collapse to hours). As MISO's data documentation states, "A constraint is a bottleneck or choke-point on the transmission network."[58] The two ISOs report shadow prices for a large number (thousands) of potential constraints, but in any given hour, most are not binding.

Whether these constraints bind, and the shadow value associated if it does bind, is of course a market outcome, not an exogenous shifter. So I do not use this as a source of identifying variation per se. However, for descriptive purposes I regress the dollar value of the allocative inefficiencies that I calculate on various measures taken from these binding constraints data. These regressions are intended to show that the variation in allocative inefficiencies is closely related to the variation in binding constraints, providing reassurance that the main results do indeed reflect transmission constraints rather than other market inefficiencies.

I calculate the 100 most binding constraints from each ISO and analyze these individually; I aggregate the rest of the constraints into summary measures. Specifically, for each of the 100 most binding constraints (calculated as the highest summed shadow price over the sample period), I create a variable equal to the shadow price in each hour (calculated as the average shadow price across all twelve 5-minute intervals). For the remaining constraints, I calculate

[58]Source: `https://misodocs.blob.core.windows.net/marketreports/Real-Time\%20Binding\%20Constraints_Real-Time\%20Binding\%20Constraints\%20Readers\%20Guide.pdf`, accessed 24 August 2024.

the count of binding constraints in each hour (i.e., the number of constraints with a shadow price not equal to zero).

I then regress hourly allocative inefficiencies on the 200 variables measuring the shadow value at each of the largest constraints, plus the two ISO-level count variables measuring the number of other binding constraints across the ISO's footprint. I will note that the constraints do include market-to-market constraints, so my right-hand side variables do capture transmission constraints that prevent flows between MISO and SPP.

Given the large number of explanatory variables, I do not show regression coefficients. But most importantly, an F-test on all 202 coefficients yields a p-value of less than 0.001, and the R2 in this regression is 0.65, indicating that observed transmission constraints are highly predictive of my constructed allocative inefficiencies.

As another way to see this, I instead regress my wedge on a count of binding constraints across MISO and SPP combined. This yields a lower R2, which is not surprising, as it drops information about how binding each constraint is. Nonetheless it useful for examining the intercept and the magnitude of the coefficient on the count variable. Results are shown in Table A20.

Table A20: Binding Constraints Predict Allocative Inefficiencies

	(1)
Count of binding constraints	7013***
	(489)
Constant	20596***
	(3476)
Observations	61,318
R^2	0.29

Note: The unit of observation is an hour. The dependent variable is the allocative inefficiencies reported in the main text. The independent variable is a count of binding constraints reported by MISO and SPP. Standard errors are clustered at the sample week.

The intercept is around \$21,000 in an hour, whereas the sample mean allocative inefficiency is around \$98,000 in an hour. That is, with zero binding constraints, this regression predicts allocative inefficiencies that are substantially less than what is observed in the typical hour. And moving from the 75th percentile of the count variable (15 binding constraints) to the 25th percentile (5 binding constraints) would imply lowering allocative inefficiencies by \$70000, which is very close to the actual difference in the 75th percentile versus the 25th percentile of the inefficiencies variable (65000). Thus overall, my observed measures of market inefficiencies are closely correlated with ISO-reported data on the binding constraints they observe in their market clearing algorithm.

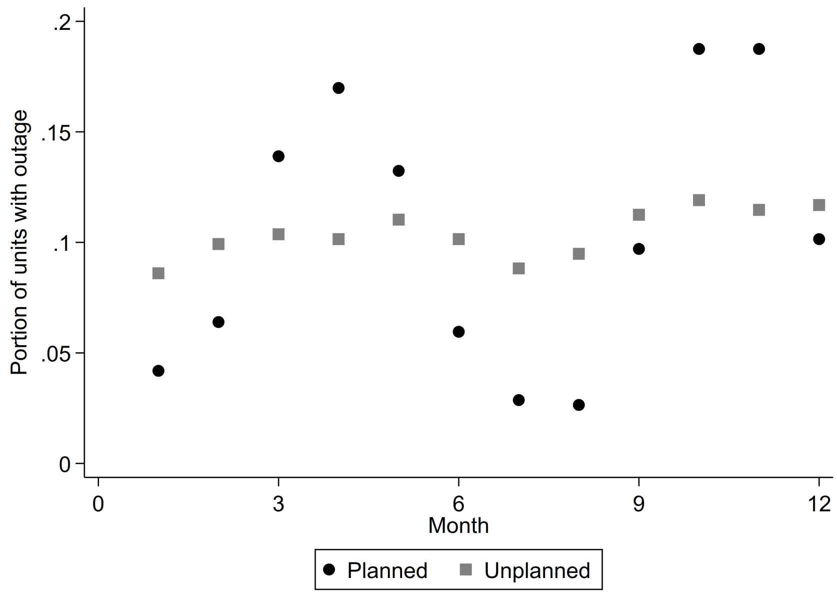
A2.5 Summarizing Model Fit

Overall, observed and modeled data fit well across generation, prices, and geographic price dispersion, whether we consider the first and second moments of each variable, correlations, or the time series. Moreover, modeled allocative inefficiencies are closely related to ISO-reported geographic price dispersion and binding constraints, two measures of transmission congestion.

A3 Outages

Generators are frequently unavailable, sometimes for planned maintenance and sometimes because of unplanned outages. Both follow a seasonal pattern; to replicate this in my model, I obtain data from Potomac Economics (2022) on the monthly distribution of each type of outage:

Figure A15: Outage Seasonality



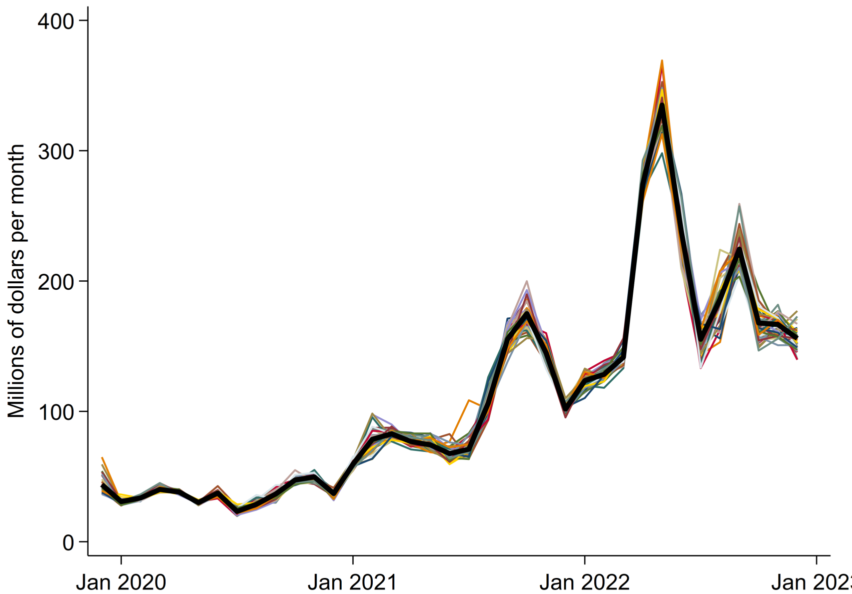
Note: This figure shows the outage rate (across months of the year) used in the main model, separated by planned versus unplanned outages.

Planned outages are coordinated across units in an ISO to prevent supply shortages. To approximate this, I derate the capacity of all units in the market by a fixed percentage in each month. This is preferred to independent stochastic draws across generators, which would lead to some hours with very little capacity available market-wide. It is preferred to correlated draws across units for computational simplicity.

Unplanned outages are, of course, not coordinated. In the main text, I apply independent stochastic draws to remove units from the dispatch queue. In this Appendix, I instead perform a Monte Carlo with 50 draws on unplanned outages. This Monte Carlo forces unplanned outages to last two weeks. Below I show that the average across the Monte Carlo draws is comparable to what I report in the main text. I also show the variation across results from different draws.

First, the level and the time path of the allocative inefficiency is the same as what is reported in Figure 2, and the uncertainty across the draws is small (Figure A16).

Figure A16: Additional Generation Costs From Spatial Constraints, Monte Carlo of Outages



Note: This figure matches Figure 2 in the main text, but with 50 draws of unplanned outages, where outages persist for two weeks.

Second, the coefficients from the regression of allocative inefficiencies on demand, fuel prices, and wind potential are on average comparable to those in Table 2, with uncertainty not too dissimilar from what is reported in Table 2's standard errors (Table A21).

Third, the coefficients from a regression of MISO South net revenues on wind potential are on average similar to those Table 3, with uncertainty not too dissimilar from what is reported in Table 3's standard errors (Table A22).

And finally, the results reported for Entergy Arkansas's and Entergy Louisiana's net revenue changes are comparable to what is reported in the main text: the mean revenue change (combined across Entergy AR and Entergy LA) is -830 million; the 25th percentile -880 million; and the 75th percentile -790 million.

Table A21: Variation in Table 2 Coefficients Across Monte Carlo Runs

Coefficient from Table 2	25th percentile	Mean	75th percentile
Panel A: Column 1 results			
Demand	0.58	0.65	0.71
Natural gas price	18305	20439	22164
Wind gen + curtailments	4.2	4.3	4.3
Panel B: Column 2 results			
Demand	0.59	0.66	0.72
Natural gas price	18224	20356	22081
Wind gen	1.10	1.18	1.26
Wind curtailments	35.4	35.8	36.2
Panel C: Column 3 results			
Demand	0.55	0.62	0.68
Natural gas price	25496	27056	28603
Wind gen + curtailments	4.5	4.6	4.7
Panel D: Column 4 results			
Demand	0.56	0.63	0.69
Natural gas price	26946	28521	30006
Wind gen	-0.12	-0.06	0.00
Wind curtailments	45.6	46.4	47.2

Note: This table reports the distribution of coefficients from 50 Monte Carlo runs on stochastic outages. Each panel reports statistics corresponding to a column of Table 2.

Table A22: Variation in Table 3 Coefficients Across Monte Carlo Runs

Coefficient from Table 2	25th percentile	Mean	75th percentile
Panel A: Column 1 results			
Potential wind gen., GWh	-1376	-1272	-1205
Panel B: Column 2 results			
Potential wind gen., GWh	-4411	-4372	-4343
Panel C: Column 3 results			
Potential wind gen., GWh	-3219	-3100	-2983

Note: This table reports the distribution of coefficients from 50 Monte Carlo runs on stochastic outages. Each panel reports statistics corresponding to a column of Table 3.

A4 Partial Integration

As reported in the robustness checks, I also assess counterfactuals with partial integration. Specifically, in these counterfactuals all regions keep their same constraint from Equation 3, except two adjacent regions are now able to trade freely with one another (but face the same constraints on trades with other regions that they do in the main constrained counterfactual). I conduct this analysis under two different sets of assumptions: assuming this integration solves the curtailments problem in both regions, or assuming it has no impact on curtailments relative to the original constrained equilibrium. The latter serves as a useful bound if, for instance, demand in the newly importing region is insufficient to absorb all wind generation from the newly exporting region.

Some caution is warranted when interpreting these results; they assume that integration of adjacent regions does not change congestion effects in the rest of the system. In reality, any change to the transmission network can impact the rest of the grid.

I conduct this analysis for all 19 pairs of regions, as listed below and shown on the map below:

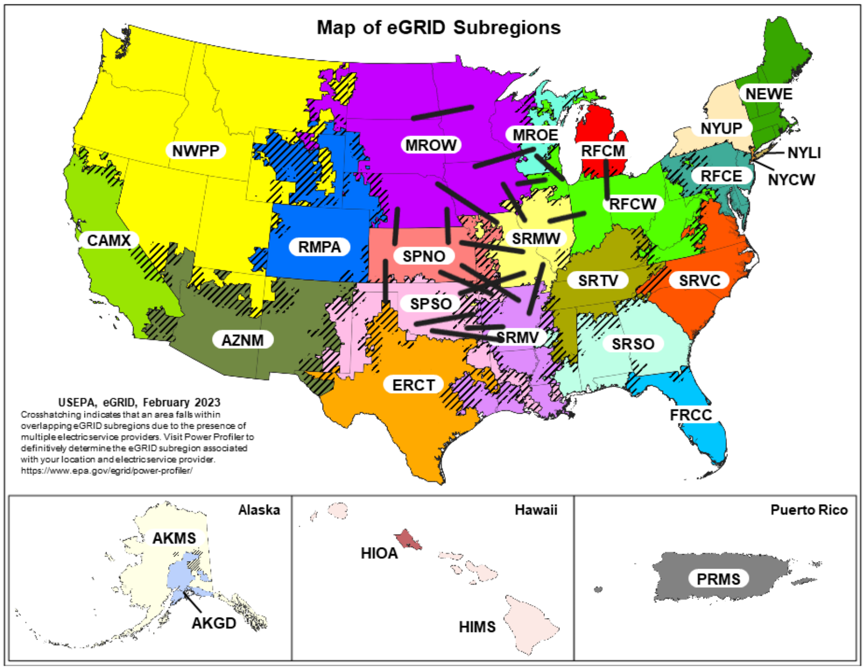
Table A23: Pairwise Integration: Connections Assessed

MISO-MROE to MISO-MROW
MISO-MROE to MISO-RFCW
MISO-MROW to SPP-MROW
MISO-MROW to SPP-SPNO
MISO-MROW to MISO-SRMW
MISO-MROW to MISO-RFCW
MISO-RFCM to MISO-RFCW
MISO-RFCW to MISO-SRMW
MISO-SPSO to SPP-SPNO
MISO-SPSO to MISO-SRMW
MISO-SPSO to MISO-SRMV
MISO-SPSO to SPP-SPSO
MISO-SRMV to MISO-SRMW
MISO-SRMV to SPP-SPNO
MISO-SRMV to SPP-SPSO
MISO-SRMW to SPP-SPNO
MISO-SRMW to SPP-MROW
SPP-MROW to SPP-SPNO
SPP-SPNO to SPP-SPSO

Note: This table lists all the pairwise integration counterfactuals assessed.

Here I describe which connection points have the most impact on allocative inefficiencies. I examine 2022 specifically, as well as the average over the study's sample period (2016-2022). And, I report changes in allocative inefficiency arising just from fossil unit re-dispatch versus additionally incorporating curtailment effects.

Figure A17: Pairwise Integration: Connections Assessed



Note: This map shows all the pairwise integration counterfactuals assessed. The underlying map is from eGRID, matching Figure A1. Black lines drawn in by the author. Recall that both SPP and MISO have footprints in the MROW subregion (similarly for SPNO and SPSO), hence the line connecting the Dakotas to Minnesota, and hence e.g. two separate lines connecting MROW to SPNO.

The biggest gains from integration across two adjacent regions come from connecting MISO-SRMV to SPP-SPNO – roughly Arkansas/Louisiana to Kansas/Missouri, whether we look at the entire time frame or just the most recent year. In this model, that yields around $560 million under 2022 conditions, or roughly one quarter of the total reported in Table 1, and substantially higher than the pairwise average of $271 million. This scenario yields substantial drops in net revenue for Entergy: $300-400 million under 2022 conditions, depending on what one assumes about how integration impacts the needs for curtailments.

Also well-above the pairwise average are the gains from connecting MISO-SRMV to SPP-SPSO or MISO-SPSO to SPP-SPNO. That is, three of the top five pairs involve connecting MISO South to nearby parts of SPP. The MISO-SRMV to SPP-SPSO integration again involves losses for Entergy; the MISO-SPSO to SPP-SPNO instead negatively impacts Cleco Power.

Thus the overall messages of the paper are corroborated with this analysis: cost savings from integration have been large in recent years, and MISO South is particularly isolated.

These pairwise integration scenarios can also be used for rough cost/benefit calculations.

Table A24: Pairwise Integration: Pairs With Largest Inefficiencies

Regional pair	\$ (millions), 2022	2022, not including curtailment effects	Annual average	Average, not including curtailment effects
Panel A: Average across all 19 pairs				
Pair-level average	271	149	111	61
Panel B: Five largest, 2022				
MISO-SRMV to SPP-SPNO	559	401	191	149
SPP-SPNO to SPP-SPSO	429	173	152	76
MISO-SRMV to SPP-SPSO	385	140	117	51
MISO-SPSO to SPP-SPNO	379	275	135	106
MISO-MROW to MISO-RFCW	370	196	169	66
Panel C: Five largest, 2016-2022				
MISO-SRMV to SPP-SPNO	559	401	191	149
MISO-MROW to MISO-RFCW	370	196	169	66
MISO-MROW to SPP-SPNO	296	88	167	58
MISO-MROW to SPP-MROW	283	98	163	60
SPP-SPNO to SPP-SPSO	429	173	152	76

Note: Panel A reports the average allocative inefficiencies (in millions of \$ per year) that could be avoided with just improved integration of adjacent regions; it averages across the 19 pairs listed in Table A23. Panel B shows the five largest pairwise inefficiencies in 2022. Panel C shows the five largest pairwise inefficiencies, averaging across 2016-2022; note that some pairs appear in both Panel B and Panel C. The four columns show four different measures of pairwise inefficiencies, separated by time period (just 2022 versus 2016-2022) and by whether curtailment effects are included.

The top five pairs in 2022 yield cost savings of \$370 to \$560 under 2022 conditions, or \$3.7 to \$5.6 billion in present value at a 10% discount rate. As a rough point of comparison, note that the CREZ project in Texas cost roughly \$7 billion (or \$9 billion in 2023 dollars), but it was more ambitious than my pairwise scenarios entail. CREZ added 18.5 GW of total transmission capacity across five major lines, each running approximately 400 miles from western to eastern Texas. The centroids of the regions I study in the pairwise scenarios are separated by a comparable distance (generally, 300 to 500 miles), but my model implies that less than 18.5 GW of capacity would be needed. So, using as the necessary capacity the maximum hourly change in generation in each region when moving to a pairwise-integrated counterfactual, the majority of my pairwise integration scenarios would pass a cost/benefit test under 2022 conditions. However, this simplified calculation ignores complications like loop flows – future research could use engineering models of the transmission grid to conduct a full cost/benefit analysis of the new infrastructure needed to integrate these regions.