

Power Flows: Transmission Lines, Allocative Efficiency, and Corporate Profits

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Supplemental Appendix

A1 Additional Tables and Figures

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

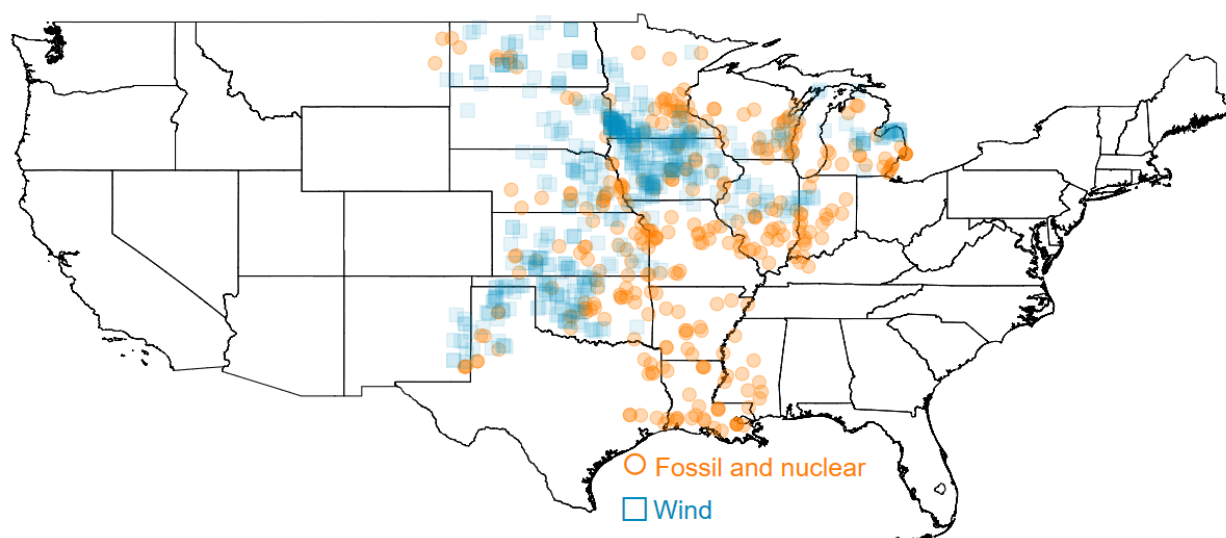
Note: This table shows the count of in-service or completed transmission upgrades, by type, reported by MISO and SPP over 2016-2022. MISO source: MISO Transmission Expansion Plan (MTEP) In Service Project List. SPP source: Quarterly Project Tracking Reports, 2016-Q1 2023.

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 (SO ₂)	53,339,178	0.69	0.46	0	1
Indicator: 1 if subject to CSAPR (NO _x)	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	61,312	331641.0	57088.9	170283	539546
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

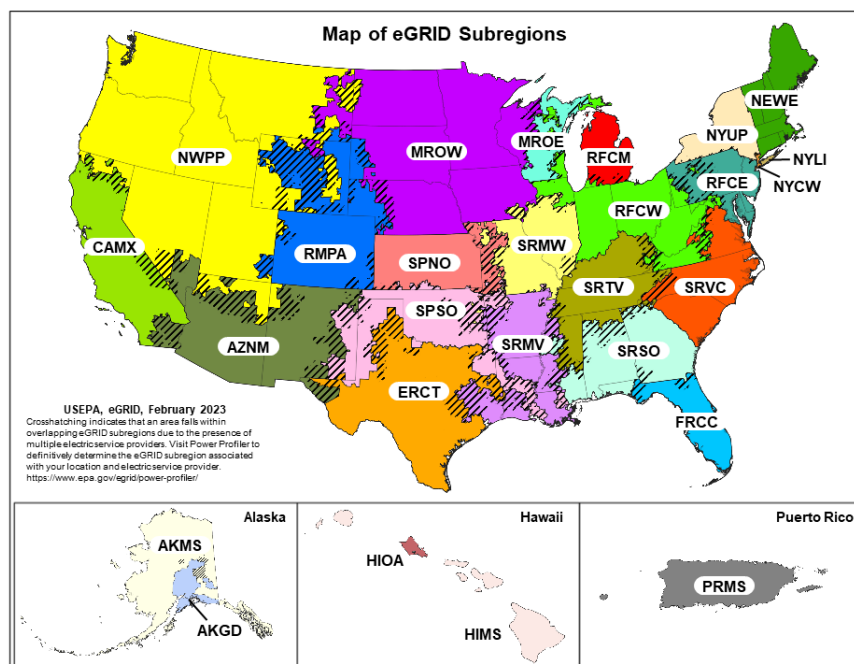
Note: This table provides summary statistics for my main estimation sample, at the generator by hour level. The sample is an unbalanced panel covering the period 2016-2022, with 993 generating units at 367 power plants. This represents all CEMS-reporting power plants (generally, fossil-fuel fired units 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



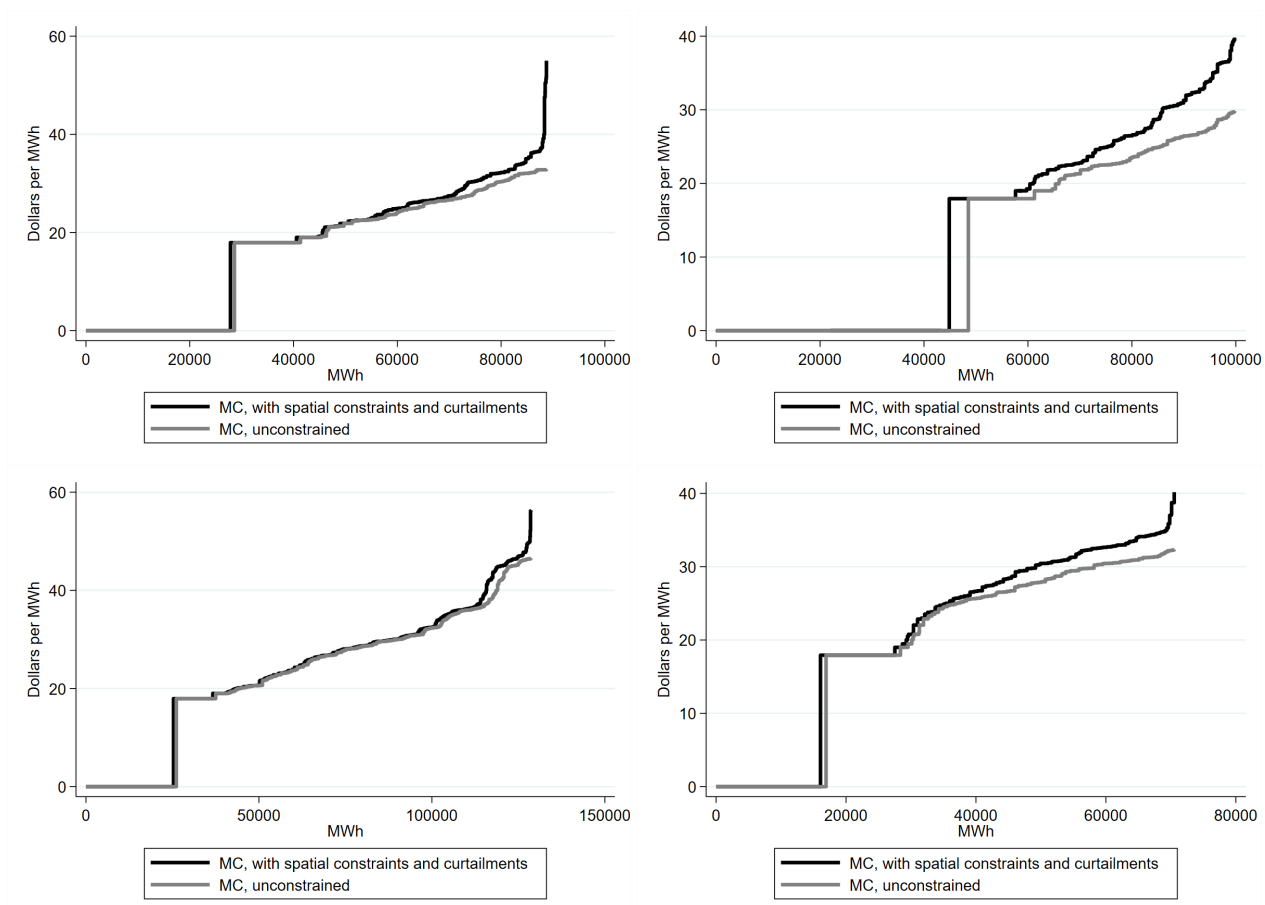
Note: This map shows the location of plants in the sample, by fuel type.

Figure A2: NERC Subregion Boundaries



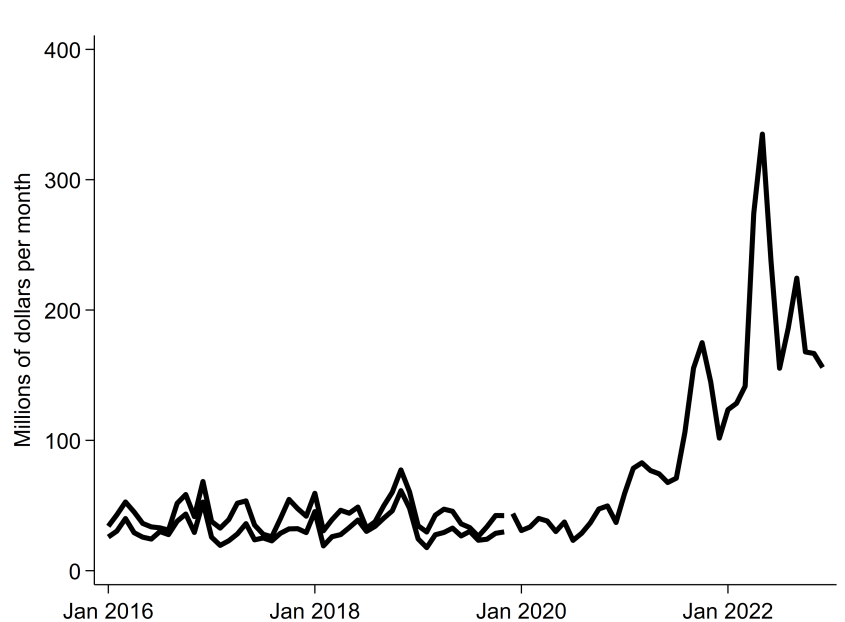
Note: This map shows NERC subregion boundaries as reported in eGRID. I interact these with a MISO versus SPP indicator to create the subregions that I implement in my main regionally-constrained counterfactual. Most of the subregions lie within only MISO or only SPP, but note that MROW has a number of 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



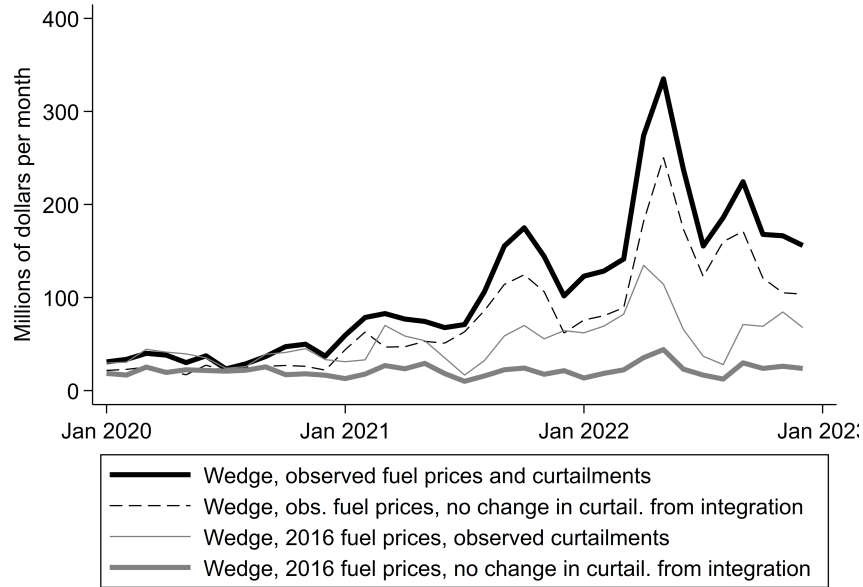
Note: This figure is constructed like Figure 1 in the main text, but showing alternative date-hour combinations. Note the scales of both axes vary across the four panels. The upper left panel shows an hour typical of the whole sample (2016 to 2022). The upper right panel shows an hour with particularly 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



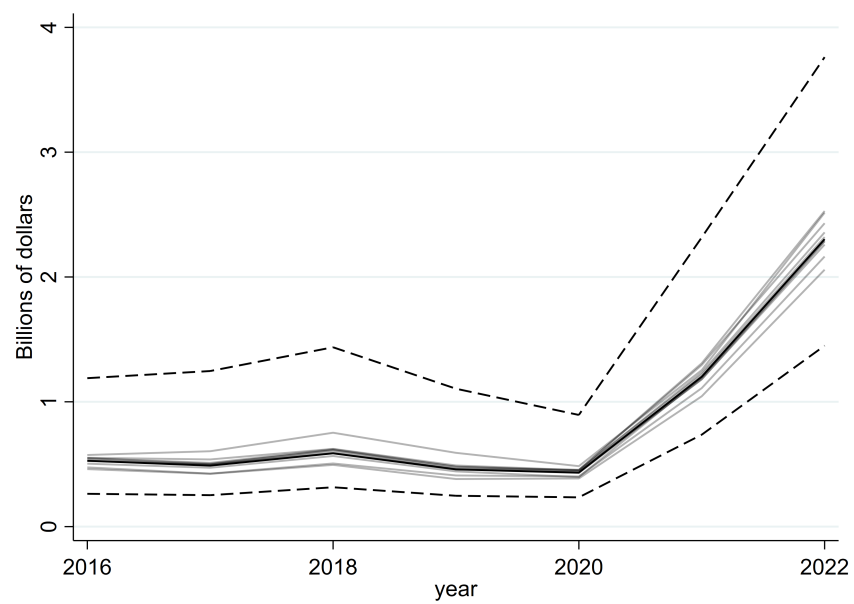
Note: This figure matches Figure 2 in the main text, but going back farther in time. For 2016 to 2019, curtailments are not observed. The two black lines for this time period show rough bounds. Specifically, the lower line assumes no wind was curtailed. In contrast, the upper line assumes the same quantity 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*** (0.086)	0.26*** (0.057)	0.65*** (0.080)	0.66*** (0.21)	0.67*** (0.086)	
Load net of nuclear gen						0.67*** (0.085)
Natural gas price	20726.7*** (2894.8)	34191.4*** (3457.4)	20357.4*** (2753.2)	34032.3*** (3838.2)	27584.3*** (2983.9)	20767.8*** (2922.6)
Oil price	216.4 (254.6)	342.8 (208.7)	222.9 (255.7)	204.3 (228.0)	189.7 (253.0)	213.4 (253.6)
Wind generation + curtailments	4.19*** (0.22)	4.81*** (0.22)	4.23*** (0.22)	4.53*** (0.25)	4.20*** (0.23)	4.19*** (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*** (0.079)	0.47*** (0.048)	0.74*** (0.073)	0.83*** (0.18)	0.67*** (0.078)	
Load net of nuclear gen						0.69*** (0.079)
Natural gas price	20643.9*** (3495.6)	31975.2*** (3236.4)	20614.4*** (3425.0)	30971.9*** (3482.8)	29536.4*** (2546.8)	20680.6*** (3524.1)
Oil price	380.6* (207.8)	237.3 (194.3)	380.8* (208.0)	62.5 (205.8)	347.6* (203.9)	377.8* (205.4)
Wind generation	1.09*** (0.12)	1.40*** (0.13)	1.10*** (0.12)	0.83*** (0.14)	1.07*** (0.12)	1.09*** (0.12)
Wind curtailments	35.9*** (1.16)	39.0*** (1.49)	35.9*** (1.16)	39.7*** (1.48)	36.1*** (1.17)	36.0*** (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 ∈ (70400, 94258]	Load ∈ (94258, 103334]	Load ∈ (103334, 114929]	Load ∈ (114929, 170985)
Panel A				
Demand	0.24 (0.18)	0.11 (0.22)	1.10*** (0.29)	0.99*** (0.17)
Natural gas price	21032.2*** (4197.0)	27460.1*** (3257.6)	28813.3*** (3735.3)	17030.9*** (1588.5)
Oil price	-165.5 (175.4)	172.9 (244.9)	357.5 (455.3)	1069.2 (793.4)
Wind generation + curtailments	4.44*** (0.22)	4.14*** (0.24)	4.26*** (0.28)	3.62*** (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*** (0.15)	0.67*** (0.15)	1.21*** (0.21)	1.05*** (0.15)
Natural gas price	23921.7*** (2726.8)	28944.8*** (2663.2)	30759.5*** (2986.0)	17074.0*** (2293.1)
Oil price	180.2 (137.9)	119.2 (203.9)	233.0 (322.6)	1140.1* (633.4)
Wind generation	0.86*** (0.097)	0.82*** (0.11)	0.66*** (0.15)	0.23 (0.24)
Wind curtailments	29.1*** (0.59)	37.4*** (1.24)	44.4*** (2.08)	61.6*** (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*** (0.074)	0.53*** (0.087)	0.41*** (0.088)	0.74*** (0.23)
Natural gas price	14138.2*** (764.9)	27446.1*** (2748.8)	29106.2*** (3295.2)	40730.4*** (3541.0)
Oil price	-37.5 (263.6)	255.2 (185.5)	409.3 (268.3)	550.2 (442.3)
Wind generation + curtailments	-0.14 (0.27)	0.79*** (0.24)	3.32*** (0.26)	8.54*** (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*** (0.073)	0.52*** (0.087)	0.42*** (0.088)	1.03*** (0.23)
Natural gas price	14079.0*** (743.1)	27532.7*** (2643.7)	29587.4*** (3098.9)	41157.3*** (2892.9)
Oil price	-31.8 (262.6)	337.2* (175.0)	573.2*** (203.6)	650.7* (333.4)
Wind generation	-0.35 (0.27)	0.23 (0.24)	1.34*** (0.20)	1.85*** (0.35)
Wind curtailments	25.6*** (4.44)	35.2*** (2.38)	39.5*** (1.89)	31.3*** (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*** (0.22)	0.99*** (0.27)	0.57** (0.26)	0.87*** (0.22)	0.80*** (0.14)	0.75*** (0.097)	0.18* (0.11)	1.01*** (0.12)
Natural gas price	18830.5*** (2799.2)	43400.0*** (8603.3)	24423.3*** (6636.8)	16188.8*** (5482.1)	17532.7*** (5740.9)	20917.2*** (3422.5)	20763.8*** (3613.7)	20877.8*** (2303.2)
Oil price	812.2 (646.8)	-361.7* (206.5)	875.8 (948.0)	229.0 (693.3)	-246.4 (435.6)	361.2 (294.3)	184.9 (257.6)	252.8 (294.7)
Wind gen. + curtail.	3.73*** (0.33)	4.72*** (0.45)	3.49*** (0.55)	4.69*** (0.43)	4.16*** (0.26)	4.19*** (0.24)	4.54*** (0.22)	3.77*** (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*** (0.18)	1.30*** (0.27)	0.64*** (0.19)	1.11*** (0.20)	0.79*** (0.13)	0.69*** (0.086)	0.41*** (0.10)	1.13*** (0.11)
Natural gas price	17820.1*** (2818.3)	38772.6*** (6300.1)	33829.5*** (5698.6)	22020.8*** (4978.6)	22800.0*** (4783.3)	20284.1*** (3646.8)	20640.8*** (4343.0)	20394.8*** (2574.2)
Oil price	415.8 (424.6)	-68.6 (182.6)	1648.9*** (618.9)	515.1 (567.7)	159.8 (388.6)	438.3** (215.9)	391.7* (213.0)	375.3 (249.1)
Wind generation	0.94*** (0.19)	1.29*** (0.21)	0.40* (0.23)	0.87*** (0.27)	1.17*** (0.17)	1.05*** (0.13)	1.31*** (0.12)	0.52*** (0.13)
Wind curtailments	34.3*** (1.25)	32.1*** (1.67)	62.6*** (5.37)	38.3*** (2.02)	33.6*** (1.54)	36.9*** (1.26)	32.8*** (0.91)	43.7*** (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

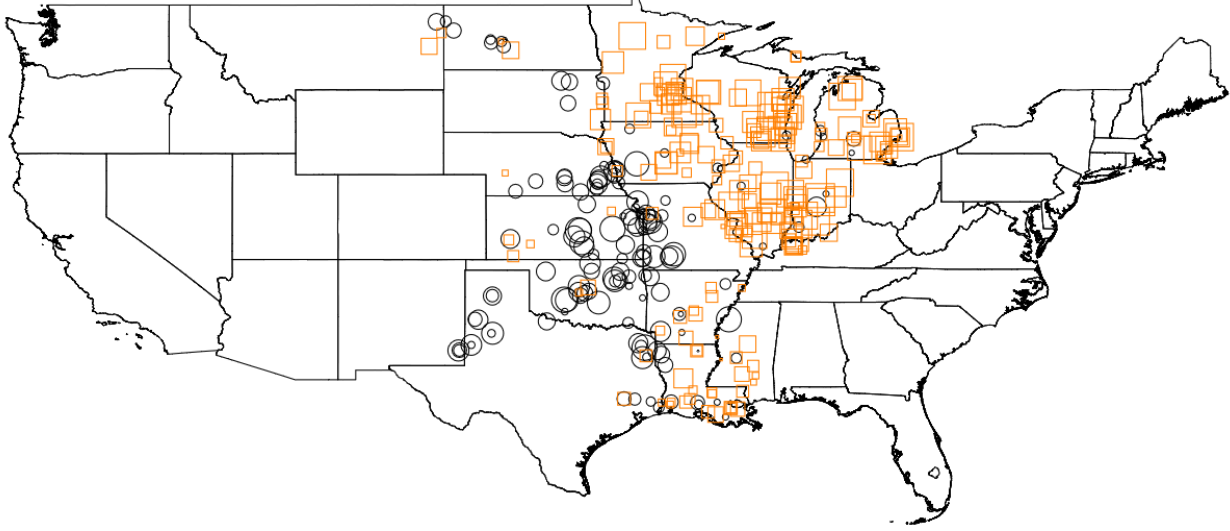
Note: Panel A of this table matches Column 1 of Table 2 in the main text, but divides the sample into four seasons, then two day types, then two hour of day types. Panel B similarly matches Column 2.

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 ($n = 231$), and the second row the portion of SPP-located plants ($n = 120$). 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*** (284)	-3026*** (247)	-3203*** (278)	-3065*** (287)	-3173*** (285)
Observations	61,276	61,276	61,276	60,604	61,276
R ²	0.18	0.18	0.13	0.19	0.18

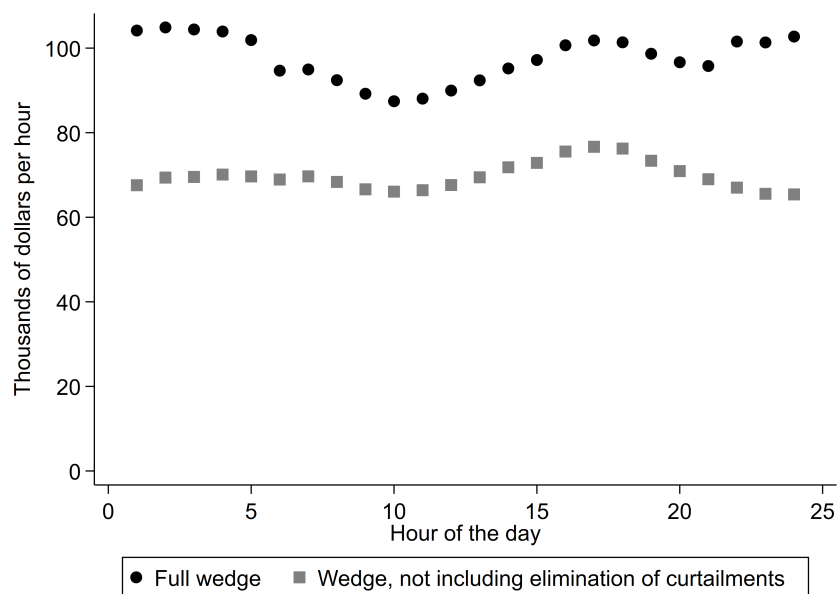
Note: This table matches Column 3 of Table 3 from the main text, but for various alternative specifications. Column 1 recreates Column 3 of Table 3. Column 2 drops the weather controls. Column 3 drops the time effects. Column 4 drops the period of Winter Storm Uri. Column 5 includes more saturated time 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	-1330*** (241)	-4415*** (283)	-3085*** (284)
Observations	61,276	61,276	61,276
R ²	0.53	0.80	0.18
Panel B: Net revenues, wind gen.			
Potential wind generation, GWh	20671*** (413)	28867*** (495)	8196*** (406)
Observations	61,276	61,276	61,276
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



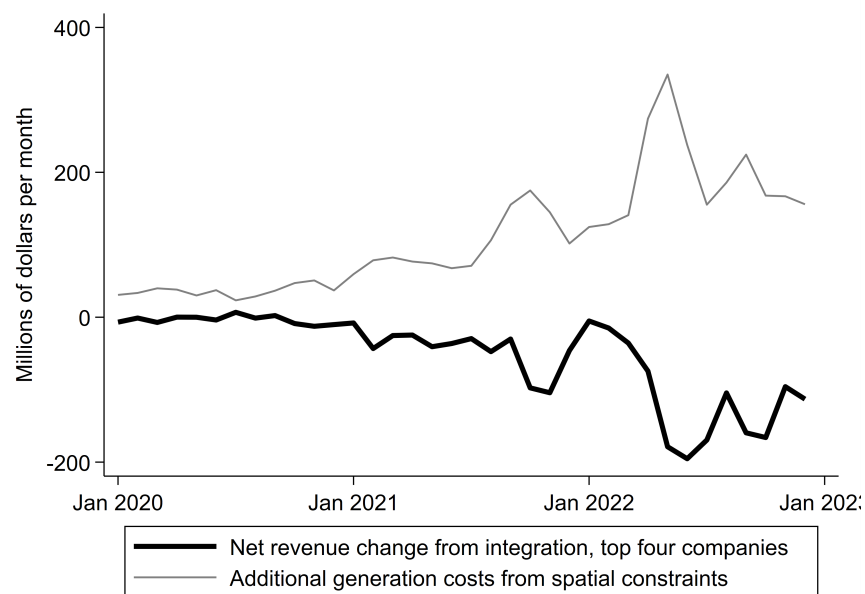
Note: This figure shows the average hourly allocative inefficiency across hours of the day. Allocative inefficiencies rise at night, but that is a function of higher curtailments rather than inefficiencies within fossil unit dispatch per se.

Figure A9: Robustness 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*** (0.19)	2.13*** (0.24)
MISO load, GWh	0.41*** (0.12)	0.30* (0.16)
Observations	59,836	59,836
R ²	0.16	0.22
Panel B: North versus Central versus South demand shocks		
North SPP load, GWh	6.93*** (1.04)	0.02 (1.11)
Central SPP load, GWh	0.68 (0.80)	1.48 (1.01)
South SPP load, GWh	-0.13 (0.42)	3.09*** (0.50)
MISO load, GWh	0.24** (0.12)	0.39** (0.16)
Observations	59,836	59,836
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*** (0.11)	-0.52*** (0.15)	-0.81*** (0.19)	0.34* (0.20)	-0.92*** (0.18)	-0.20 (0.16)	0.48** (0.20)	0.49* (0.25)
MISO load, GWh	0.88*** (0.17)	1.25*** (0.14)	1.36*** (0.19)	1.17*** (0.19)	1.46*** (0.18)	1.17*** (0.12)	1.09*** (0.23)	0.93*** (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 (0.50)	-1.16*** (0.39)	-1.52*** (0.52)	-0.20 (0.82)	-1.48*** (0.44)	3.47*** (0.48)	-0.51 (0.77)	0.73 (1.17)
Central MISO load, GWh	0.84*** (0.22)	2.32*** (0.21)	2.36*** (0.32)	0.58* (0.30)	2.81*** (0.28)	0.53*** (0.17)	0.78*** (0.29)	0.98** (0.43)
South MISO load, GWh	3.07*** (0.76)	0.79* (0.47)	1.71*** (0.63)	4.75*** (0.71)	0.77* (0.44)	0.38 (0.32)	4.03*** (0.85)	1.00 (3.30)
SPP load, GWh	0.07 (0.15)	-0.18 (0.17)	-0.59*** (0.22)	-0.27 (0.24)	-0.48** (0.18)	-0.27 (0.17)	0.02 (0.24)	0.49 (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.

⁵⁵Buchsbaum, J., Hausman, C., Mathieu, J. L., and Peng, J. “Spillovers from ancillary services to wholesale 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

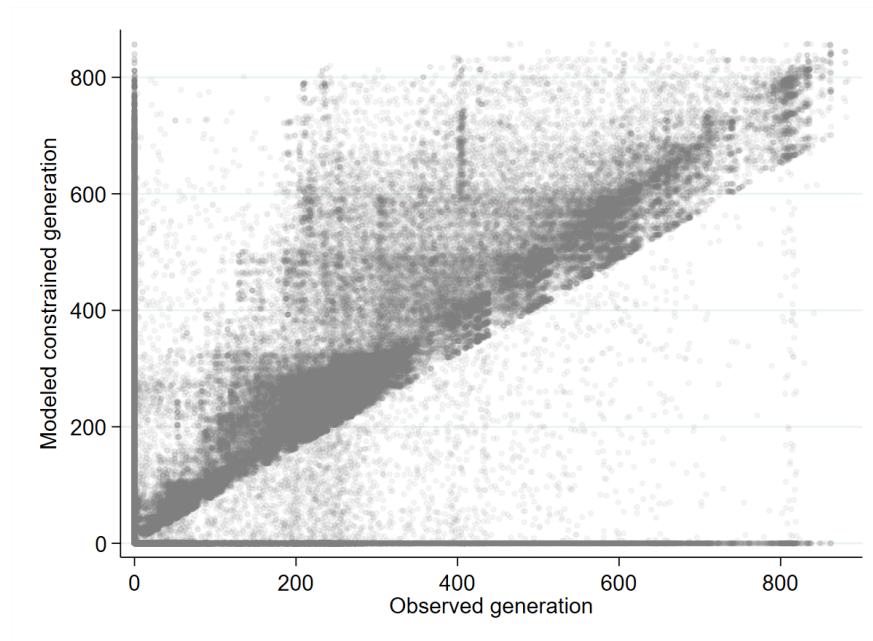
Note: This table mimics A15, but limits the sample to 6 pm weekday hours (when demand is typically higher) at low marginal cost ($\leq \$30/\text{MWh}$) units (which are likely to be dispatched).

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	0.67
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	16,415,923	39.99	60.28	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	16,414,569	40.00	60.28	24.08	29.89	41.91
Modeled constrained price	16,414,569	39.38	33.11	28.59	32.90	41.12
Modeled unconstrained price	16,414,569	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

⁵⁶Note 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.

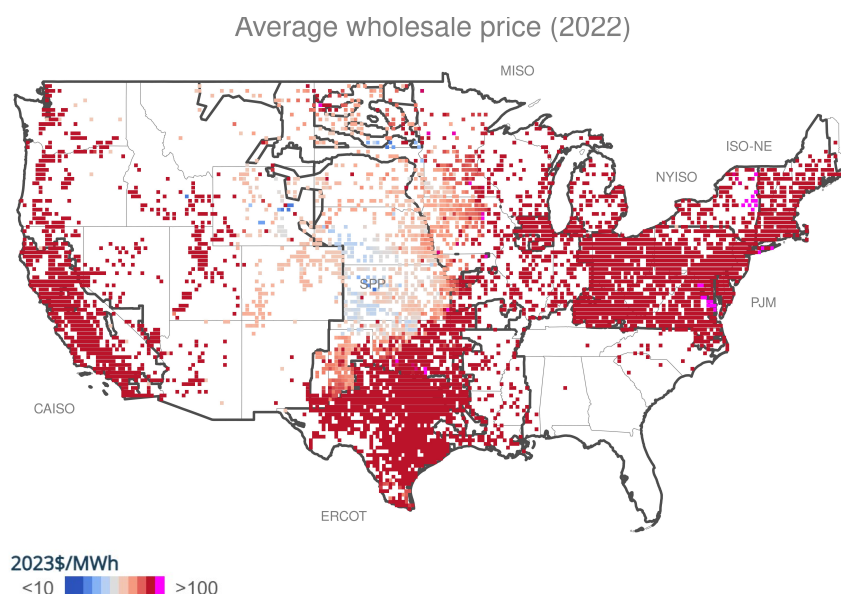
A2.3 Observed versus modeled geographic price dispersion

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

⁵⁷For 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



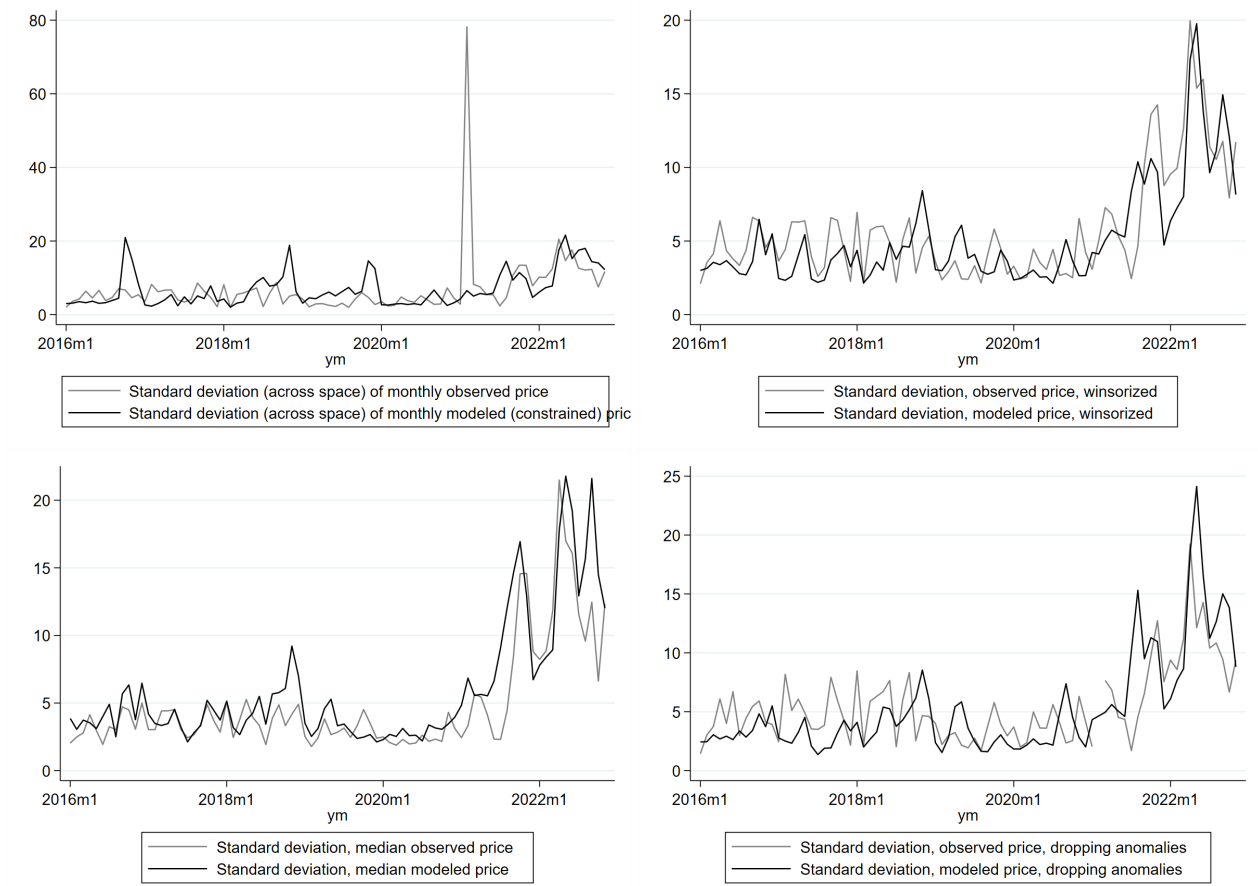
Note: This figure shows annual average prices for 2022, from Millstein, O'Shaughnessy and Wiser (2024).

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).

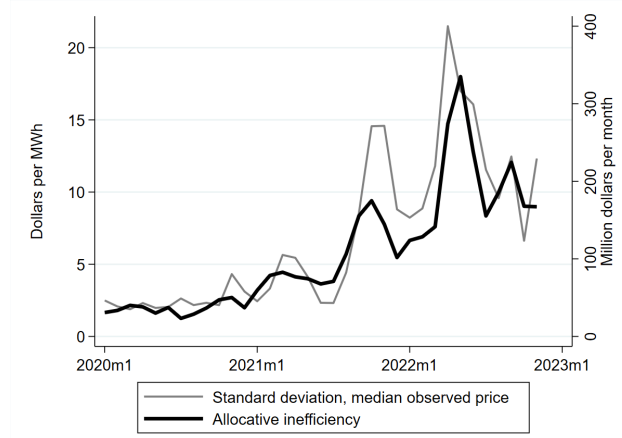
modeled price dispersion. One might worry that these anomalies drive the main results. So, a robustness check in the main paper show that the main results are similar with winsorized prices.

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*** (0.000019)	0.00038*** (0.000019)	0.00037*** (0.000018)	0.00037*** (0.000018)
Natural gas price	3.35*** (0.58)	3.34*** (0.53)	2.16** (0.87)	2.19** (0.86)
Oil price	-0.031 (0.032)	-0.015 (0.030)	-0.011 (0.030)	-0.0052 (0.030)
Wind generation + curtailments	0.00028*** (0.000019)		0.00032*** (0.000024)	
Wind generation		0.000058** (0.000023)		0.00022*** (0.000040)
Wind curtailments		0.0026*** (0.00016)		0.0013*** (0.00033)
Observations	60,504	60,504	56,092	56,092
R ²	0.23	0.24	0.08	0.09
K-P F-stat			170	20

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

⁵⁸Source: 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 mar-

ket inefficiencies are closely correlated with ISO-reported data on the binding constraints they observe in their market clearing algorithm.

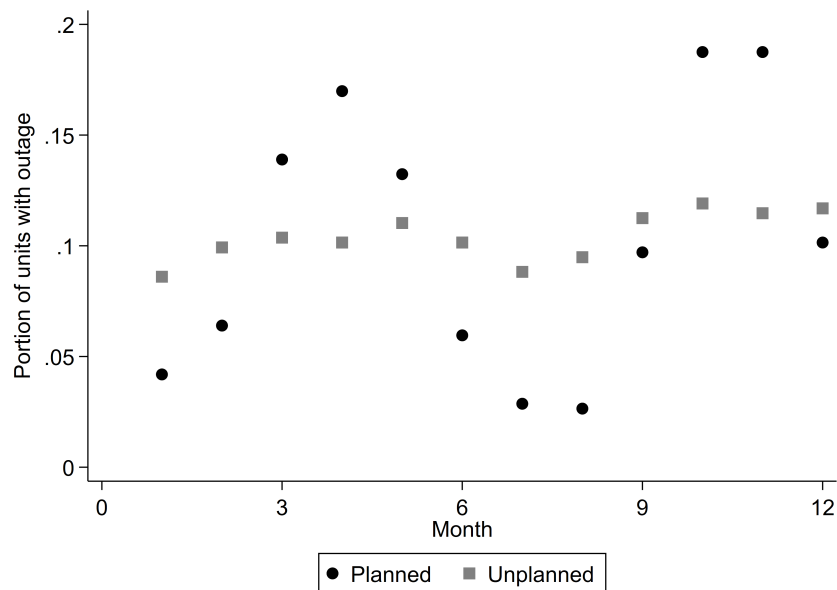
A2.5 Summarizing Model Fit

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



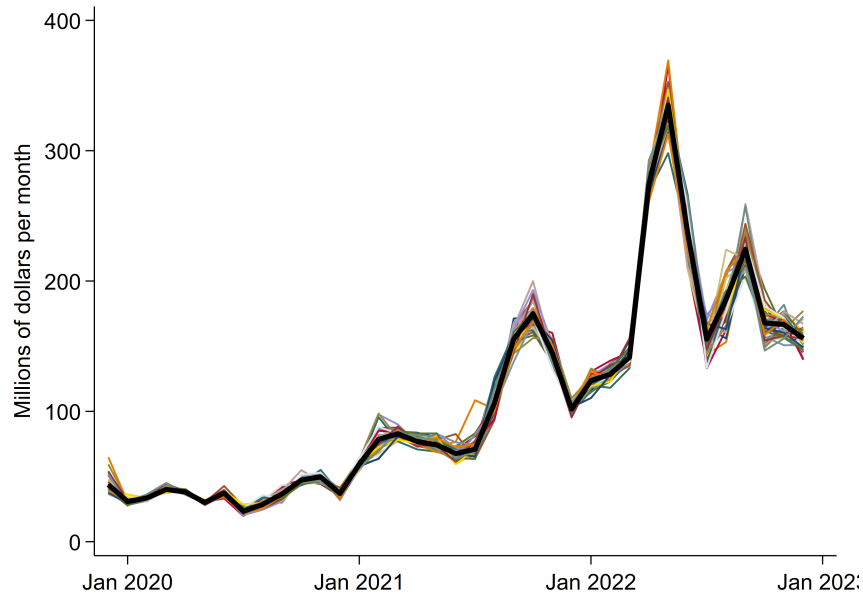
Note: This figure shows the outage rate (across months of the year) used in the main model, separated by planned versus unplanned outages.

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:

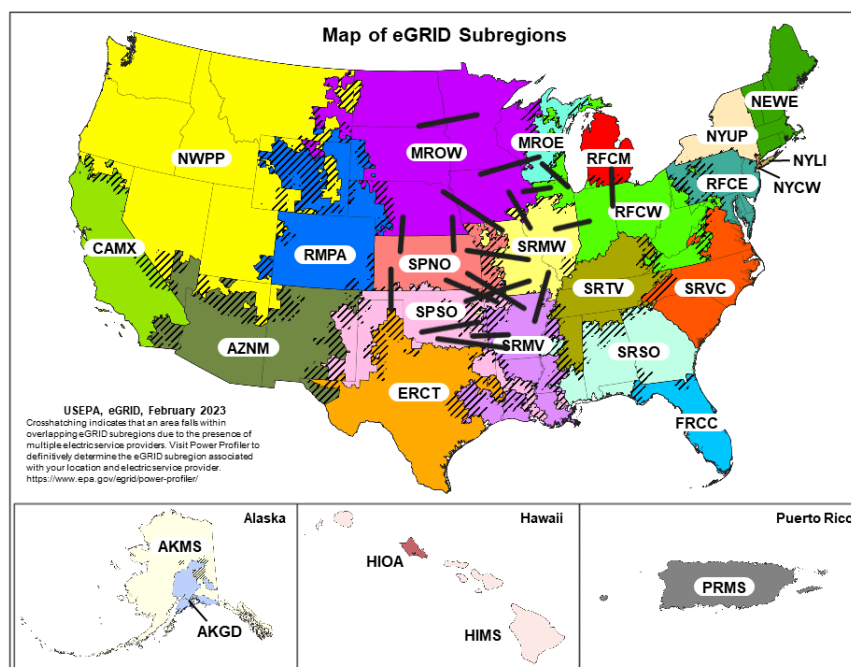
Table A23: Pairwise Integration: Connections Assessed

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.