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Coalition Stability in PJM: Exploring the Consequences of State Defection from the Wholesale Market

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ABSTRACT

Using a simulation tool, we investigate the effects created by a US state defecting from the wholesale electricity market in PJM, an organized electric grid in the eastern United States, on the states that remain in the coalition. We find, generally, that if a net-importing state defects from the wholesale energy market, the remaining states' producers are worse off and the remaining states' consumers are better off. The opposite effect takes hold if the defecting state is a net-exporter. Furthermore, we find evidence that defection impacts the remaining states' climate initiatives. The effectiveness of electric vehicle and solar photovoltaic policies are conditional on the number and characteristics of defecting states. Our simulations suggest that, for state legislatures pursuing these climate goals, the best strategy to adopt is to pass laws that are both geographically targeted and flexible.

Keywords: PJM, RTO, electricity, coalition stability, defection, energy regulation

INTRODUCTION

Since the late 1990s, organized electricity markets in the United States have shown that a geographically broad and resource-diverse power grid can achieve significant efficiency improvements in electricity power generation. These markets' success has motivated some new efforts to modify electricity structure and operations in several areas. For example, members of the Western Interconnection are considering the expansion of their current cooperative arrangement to include a day-ahead market, and in the southeast, talks between Southern Company and Duke Energy have opened regarding the formation of a Southeastern regional transmission organization (RTO). PJM, an RTO in the eastern United States, has grown from three utilities operating in the area between Philadelphia and Baltimore to the largest organized electricity grid in the Western Hemisphere.

Yet, with each additional member to the consortium, the diversity of objectives and incentives grows. The resultant conflict can add instability to the organization. Some parties may threaten to leave the coalition in response to changes in the incentive structure and underlying dynamics (both political and economic) of the member groups. It is precisely this instability that this paper seeks to explore as members consider leaving the wholesale energy market of an RTO in response to constraints imposed to limit their alternatives in implementing their environmental policies. Using an energy market simulation tool, we measure the impact on the various stakeholders that would remain if a state were to exit the wholesale electricity market in PJM. Our analysis identifies the effects of state defection to remaining suppliers and consumers and makes claims about the welfare created or destroyed by a state defection. We also explore the consequences of one state's defection on the remaining states' abilities to implement meaningful environmental policies in their electricity sectors.

The idea of a state defecting from an RTO like PJM or defecting from some portion of the markets administered by these organizations is not contrived. Recent threats from New Jersey and Maryland to withdraw from the capacity market in PJM have gained traction in the public discourse, appearing with some frequency in trade publications (Morehouse 2020; Walton 2020). The arguments for leaving the PJM capacity market focus on the disconnect between what the states—New Jersey and Maryland—are pursuing to achieve net-zero carbon goals and the actions from federal agencies—namely the Federal Energy Regulatory Commission (FERC)—to regulate the PJM capacity market. However these specific disagreements are resolved, the possible discordance between state policy goals and federal market oversight in an RTO highlights the more general complicated interactions between the various stakeholders and is thus worthy of further exploration.

The countervailing ambitions seen among New Jersey, Maryland, PJM, and FERC are not unique in the landscape of the US electricity grid. Leaders in Connecticut have leveled broadsides at another RTO, ISO-New England (ISO-NE), intimating that Connecticut might leave ISO-NE entirely because of a "lack of leadership on carbon" (Skahill 2020; Spiegel 2021). Ironically, almost simultaneous to these discussions on the Eastern Seaboard regarding partial or full defections of different states from their respective RTOs, there are calls for Western states to create a true RTO out of existing interstate arrangements (Hansen and Howe 2020). Indeed, since the creation of RTOs as prescribed by FERC Order No. 2000,1 conflicts have been prolific and almost genetic. In a remarkable legislative memo written in 2003, the author describes the plays and counterplays of American Electric Power (AEP), a transmission company

[1] FERC Order No. 2000 was issued on December 20, 1999.

headquartered in Ohio, as the company followed a FERC-imposed mandate that it place its assets under the control of an RTO:

> *"Instead of choosing either the forming Midwest ISO or the existing PJM Interconnection, AEP joined with other utilities and proposed to form the for-profit Alliance RTO, a plan FERC ultimately rejected. In 2002, FERC approved the former Alliance utilities' commitments to join either MISO or PJM…. In 2003, FERC accepted revisions to the PJM tariff that would allow AEP… to join PJM. Subsequently, however, the Kentucky Public Service Commission and the Virginia legislature prevented transfer of AEP's transmission facilities to PJM, while at the same time, state legislation in Ohio and Michigan required AEP join an RTO." (Wiese 2003)*

Over the course of a few years, AEP was required to join an RTO, blocked by the federal government from forming their own RTO, approved by the federal government to join PJM, blocked by the commissioners of Kentucky and the people of Virginia from joining PJM, and directed by the people of Ohio and Michigan to join an RTO. If ever there were a sentence that describes the complicated stakeholder interfaces embedded in an RTO, that was it.[2]

The growing interest by state leadership to leave some (or all) of an RTO's markets is interesting in its own right. We extend this analysis by reckoning with the idea that a state may, as a matter of sovereignty, remove itself from a particular RTO market, but that choice has spillover effects on the welfare of the states that remain. In the entanglement of organized electricity markets, there are states that have made no indication of defecting from RTO markets. Will that sentiment change if another state decides to defect first? How stable is an electricity transmission coalition?

Our research is the first that attempts to understand RTO stability under a wholesale energy market defection, contributing to the literature that has analyzed the impact of a capacity market defection. The independent market monitor that oversees PJM, for instance, has found that the proffered threats by New Jersey and Maryland to leave the PJM capacity market would annually cost the states as much as $386.4 million and $206.6 million, respectively (Monitoring Analytics 2020a, 2020b). Furthermore, Monitoring Analytics found that a New Jersey or Maryland defection would decrease capacity market prices that cleared in PJM post-defection. As such, our intuition of these machinations suggests that a New Jersey or Maryland defection from the PJM capacity market would make the producers in the states that remain in PJM worse off but make the consumers in the states that remain better off. This work will extend these lines of inquiry to PJM's wholesale market.

We analyze not only the impacts on producers and consumers induced by a state-driven wholesale electricity market defection,[3] but also the influence a defection of this type will have on the ability of remaining states to pursue effective net-zero carbon policies. Will states be more effective or less effective at pursuing their own environmental initiatives after another state defects from PJM's wholesale energy market? Or broadly, how are climate goals entangled between states?

To fully investigate these questions, we first begin by simulating PJM's wholesale electricity market as it was in 2019. This base case is compared to five different state-exit scenarios: New Jersey defects,

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[2] AEP, along with Commonwealth Edison and Dayton Power & Light, ended up joining PJM in 2004 (PJM n.d.).

[3] There is a slight nuance here. Institutionally, a utility is the prime agent that chooses to defect but that "choice" can be forced by the state. In modeling a state-driven defection, we mean only to analyze the result of that defection and not the political negotiations between an in-state utility and that state's regulatory and political apparatus.

Maryland defects, Virginia defects, Pennsylvania defects, and Illinois defects. We chose New Jersey and Maryland for the public comments indicating these states' distaste for recent developments in PJM's market rules. Our choice of Virginia arises because it is the largest importer of electricity in PJM and we wanted to explore the impact of defection by that extremum. Pennsylvania and Illinois, as the two largest exporters in PJM, were simulated as defectors as well. In comparing these defection scenarios to the base case, we can measure how one state's absence can influence the outcomes in other states in the consortium. Our general findings are that when a net importing state defects, the remaining states' producers are worse off and the remaining states' consumers are better off. We find an opposite effect under a scenario where the defector is a net exporter.

In the next section we introduce our simulation tool and describe the data we use for this study. In Section 3 we present our results. Section 4 offers a discussion and suggestions to extend this research. Section 5 concludes.

METHODS AND DATA

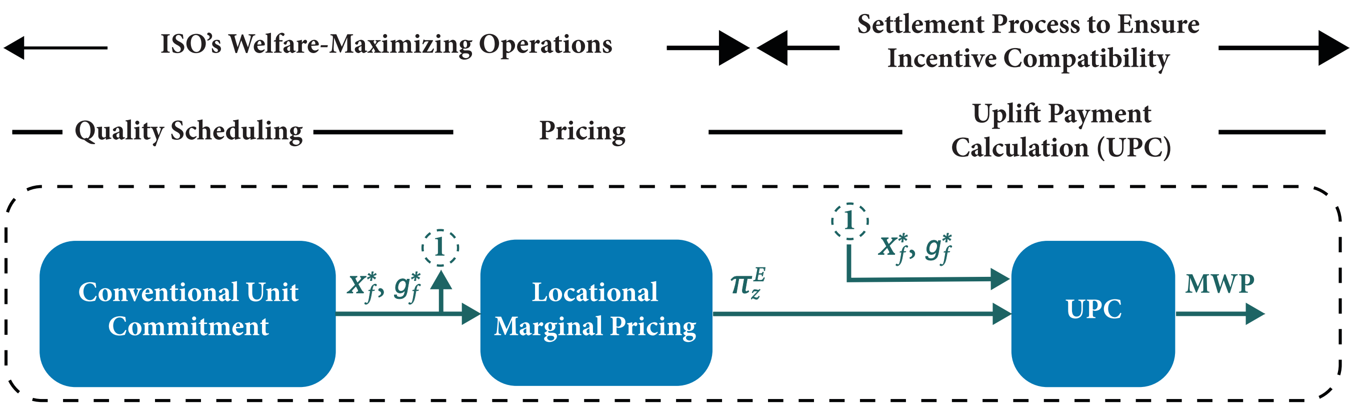
We simulate PJM's wholesale market as it was in 2019 with generator offers, merit order, ancillary services, make-whole payments, and congestion-related effects all playing a role in which generators get dispatched and what price clears in each hour of the year. To measure the impacts of a state defecting from the consortium, we also simulate the removal of a single state from the broader PJM organized market. In those defection scenarios, we simulate PJM without the supply or demand of the defecting state.

We use the Electricity Market Simulation Tool (EMST) to simulate the day-ahead market operation outcomes in PJM. EMST is a reconfigurable tool that can integrate various unit commitment and dispatch models in different ways to represent various designs in energy and ancillary service markets. The tool can calculate dispatch and financial outcomes for all individual market players including out-of-market uplift payments. EMST was first introduced by Daraeepour et al. (2019) to simulate the operation of day-ahead and real-time markets for a year-long period under different market designs that account for the characterization of uncertainty in the day-ahead markets. The tool initially explored load-following capability products, stochastic residual unit commitment, and stochastic market clearing. EMST was further extended by Daraeepour et al. (2020) to include alternative pricing mechanisms, including primal approximations of convex hull pricing.

EMST simulates the day-ahead market operations for each hour of each day and uses its commitment and dispatch outcomes to initialize simulations of the subsequent day; the algorithm's framework is shown in Figure 1. Three models are used to simulate market operations. First, EMST runs the unit commitment model to determine the generating units' optimal on/off status and scheduled electrical power output. This mixed-integer linear program takes generators' supply bids[4] along with demand and wind generation forecasts for the next 24 hours as inputs to find the schedules that minimize electricity generation costs. A second model is a linear program that performs economic dispatch, freezing the commitment variables to the optimal values found in the unit commitment and determining prices for energy and ancillary services. Prices are set equal to the shadow price of nodal balance constraints that enforce the equality of demand and supply for each period. After the market-clearing schedules and prices are determined, a third model calculates the out-of-market uplift payments that the PJM gives to generators to ensure they do not operate at a loss when following the dispatch instructions.

[4] We assume all generators offer supply bids at their marginal costs.

Figure 1. Configuration of EMST for simulating PJM market operation outcomes



x_f^*, g_f^*: ISO's Welfare-Maximizing Commitment, generation schedules

π_z^E: Zonal Energy Prices

MWP_{CD}: Make-whole payment for each individual generator to make generators whole to their operation cost so they do not operate at loss when following ISO's schedules

2.1 Models

What follows is a detailed formulation of the unit commitment, economic dispatch, and uplift payment models that are used in EMST to simulate the market operation outcomes.

2.1.1 Notation

2.1.1.1 Sets

Φ^F	Set of all fossil-fired generators, $f \in \Phi^F$ running from 1 to N_F
Φ^N	Set of all nuclear generators, $n \in \Phi^N$ running from 1 to N_N
Φ^H	Set of all hydro generators, $h \in \Phi^H$ running from 1 to N_H
Φ^K	Set of all storage units, $k \in \Phi^K$ running from 1 to N_K
Φ^S	Set of all solar generators, $s \in \Phi^S$ running from 1 to N_S
Φ^W	Set of all wind generators, $w \in \Phi^S$ running from 1 to N_S
Φ^T	Set of time periods, $t \in \Phi^T$ running from 1 to N_T
Φ^Z	Set of all zones z, $z \in \Phi^Z$ running from 1 to N_Z
Λ_z^F	Set of all fossil-fired generators in zone z, $z \in \Phi^Z$
Λ_z^N	Set of all nuclear generators in zone z, $z \in \Phi^Z$
Λ_z^H	Set of all hydro generators in zone z, $z \in \Phi^Z$
Λ_z^K	Set of all storage units in zone z, $z \in \Phi^Z$
Λ_z^S	Set of all solar generators in zone z, $z \in \Phi^Z$
Λ_z^W	Set of all wind generators in zone z, $z \in \Phi^Z$
Λ_z^{NZ}	Set of neighboring zones interconnected to zone z, $z \in \Phi^Z$

2.1.1.2 Parameters

$S_f^C(t)$	Start-up cost of generator f in period t (\$/start)
$N_f^C(t)$	No-load cost of generator f in period t (\$/hour)
$V_f^C(t)$	Variable fuel cost of generator f in period t (\$/MWh)
$\overline{P}_f$	Maximum power output of generator f (MW)
$\underline{P}_f$	Minimum power output of generator f (MW)
R_f^{SU}	Startup ramp-rate of generator f (MW/hour)
R_f^{SD}	Shutdown ramp-rate of generator f (MW/hour)
R_f^{OP}	Operating ramp-rate of generator f (MW/hour)
MT_f^U	Minimum uptime of generator f (hour)
MT_f^D	Minimum downtime of generator f (hour)
$\overline{P}_f^{dis}$	Maximum power injection from energy storage unit k when discharging (MW)
$\overline{P}_k^{char}$	Maximum power withdrawal from energy storage unit k when charging (MW)
$\overline{E}_k$	Energy storage capacity of storage unit k (MWh)
E_k^{ini}	Energy stored by storage unit k at the beginning of the scheduling horizon (MWh)
α_k	A non-negative factor to control stored energy in energy storage system k for the next time horizon
η_k^{dis}	Discharging efficiency of energy storage unit k; for pumped-hydro units, $\eta_k^{dis} = 1$
η_k^{ch}	Charging efficiency of energy storage unit k; for pumped-hydro units, this equals the ratio of energy injected to energy withdrawn
η_k^{loss}	Self-discharge losses for storage unit k; for pumped-hydro units, $\eta_k^{loss} = 0$
μ_k	Power to energy ratio of storage technology k
$\overline{P}_w(t)$	Day-ahead forecast of electricity output from wind farm w at time t (MWh)
$\overline{P}_s(t)$	Day-ahead forecast of electricity output from solar farm s at time t (MWh)
$\overline{P}_h(t)$	Day-ahead electricity output forecast for hydro plant h at time t (MWh)
$\overline{L}_z(t)$	Electricity demand in zone z in period t (MWh)
$P_{z,nz}^{exp}(t)$	Scheduled energy exports from zone z to zone nz in period t (MWh)
$P_{z,nz}^{imp}(t)$	Scheduled energy imports to zone z from zone nz in period t (MWh)
$\overline{P}_{z,nz}^F$	Transmission capacity between zones z and nz (MW)
MWP_f	Total make-whole payments made by PJM to generator f for $\forall t \in \Phi^T$ (\$)

2.1.1.3 Continuous Optimization Variables

$p_f(t)$	Scheduled production for fossil-fired generator f in period t (MWh)
$p_n(t)$	Scheduled production for nuclear plant n in period t (MWh)
$p_h(t)$	Scheduled production for hydro plant n in period t (MWh)
$p_k^{ch}(t)$	Scheduled electricity withdrawal to charge storage unit k at time t (MWh)
$p_k^{disc}(t)$	Scheduled electricity injection from the discharge of storage unit k at time t (MWh)
$e_k(t)$	Energy stored in storage unit k at time t (MWh)
$p_s(t)$	Scheduled production for solar farm s in period t (MWh)
$p_w(t)$	Scheduled production for wind farm w in period t (MWh)
$F_{z,nz}(t)$	Scheduled active power flow between nodes $z \in \Phi^Z$ and $nz \in \Lambda_z^{NZ}$ at time t (MWh)

2.1.1.4 Set of Binary Optimization Variables

$x_f(t)$	On/off status schedule of generator f in period t
$u_f(t)$	Startup schedule of generator f in period t
$d_f(t)$	Shutdown schedule of generator f in period t
$v_k(t)$	Discharging status of storage unit k at time t; 1 if discharging, 0 otherwise
$y_k(t)$	Charging status of storage unit k at time t; 1 if charging, 0 otherwise

2.1.1.5 Dual Optimization Variables

$\pi_{Z,t}^{LMP}$	Locational marginal price for energy in zone z period t ($/MWh)

2.1.2 Unit Commitment Formulation

Equations (1a) through (1t) represent the formulation of the unit commitment model. Equation (1a) represents the model's objective function, which is to minimize total electricity production costs. Each term of the expression $V_f^C(t) \times p_f(t) + N_f^C(t) \times x_f(t) + S_f^C(t) \times u_f(t)$ represents generator f's variable fuel costs, no-load costs, and startup costs, respectively. Equation (1b) enforces nuclear generators to run at their maximum generation limit consistent with their operation as baseload resources. Equations (1c) through (1d) limit the generation of wind and solar producers to their day-ahead forecast. Equation (1e) ensures hydro generation schedules remain equal or below the prespecified schedules provided by the plant operators. Equations (1f) through (1l) represent fossil-fired generators' technical electricity generation constraints. Equation (1f) represents lower and upper generation bounds for fossil-fired producers. Equations (1g) and (1h) represent generators' up- and down-ramp rate limits during normal, startup, and shutdown operations. Equation (1i) represents a state-transition constraint that makes a generator's ON/OFF status transition coherent with its corresponding startups and shutdowns. Equations (1j) through (1k) enforce the generators' required minimum uptime and downtime limits. These are included because ensuring reliable and economical generator operations requires keeping them online/offline for a minimum length of time after a startup/shutdown. Equation (1l) declares that the commitment, startup, and shutdown variables are binary.

Equations (1m) through (1p) model the operating limits of storage units in the commitment problem. Equation (1m) guarantees that a storage unit does not operate in discharging and charging mode simultaneously. Equation (1n) limits a storage unit's scheduled power injection to be less than or equal to its discharging capacity. Equation (1o) ensures a storage unit's scheduled power withdrawal does not exceed its maximum charging capacity. Equation (1p) sets the energy stored in storage unit k at time t

equal to the energy stored at time $t-1$, minus the energy discharged, plus the energy charged, minus the self-discharge losses. Equation (1q) declares variables that represent charging and discharging status of the storage to be binary. Equation (1r) represents the zonal balance constraint that enforces the balance of active power in all zones such that the total energy that is injected into a zone and the total energy that is withdrawn from that zone are equal at any time. Equations (1s) and (1t) enforce active power flow between transmission zones to be within transmission capacity limits between zones.

$$\underset{P_{f,t},x_{f,t},u_{f,t},d_{f,t},P_{n,t},P_{s,t},P_{w,t},P_{f,t},p_{k,t}^{ch},p_{k,t}^{disc},e_{k,t},v_{k,t},y_{k,t},F_{n,m,t}}{\text{Min}} \sum_{t\in\Phi^T}\sum_{f\in\Phi^F}\left(V_f^C(t)\times p_f(t)\right)+N_f^C(t)\times x_f(t)+S_f^C(t)\times u_f(t)) \tag{1a}$$

Subject to:

$$p_n(t)=\overline{p}_n\ \forall n\in\Phi^N,\forall t\in T \tag{1b}$$

$$0\le p_w(t)\le\overline{P}_w(t)\ \forall w\in\Phi^W,\forall t\in T \tag{1c}$$

$$0\le p_s(t)\le\overline{P}_s(t)\ \forall s\in\Phi^S,\forall t\in T \tag{1d}$$

$$0\le p_h(t)\le\overline{P}_h(t)\ \forall h\in\Phi^H,\forall t\in T \tag{1e}$$

$$\underline{P}_f\, x_f(t)\le p_f(t)\le\overline{P}_f\, x_f(t)\ \forall f\in\Phi^F,\forall t\in T \tag{1f}$$

$$p_f(t)-p_f(t-1)\le R_f^{OP}x_f(t-1)+R_f^{SU}u_f(t)\ \forall f\in\Phi^F,\forall t\in T \tag{1g}$$

$$p_f(t-1)-p_f(t)\le R_f^{OP}x_f(t)+R_f^{SD}d_f(t)\ \forall f\in\Phi^F,\forall t\in T \tag{1h}$$

$$u_f(t)-d_f(t)=x_f(t)-x_f(t-1)\ \forall f\in\Phi^F,\forall t\in T \tag{1i}$$

$$x_f(t)\ge\sum_{r=t-MT_f^U+1}^{t}u_f(r)\ \forall f\in\Phi^F,\forall t\in T \tag{1j}$$

$$x_f(t)\le 1-\sum_{r=t-MT_f^D+1}^{t}d_f(r)\ \forall f\in\Phi^F,\forall t\in T \tag{1k}$$

$$x_f(t)\in\{0,1\},u_{i,t}\in\{0,1\},d_{i,t}\in\{0,1\}\ \forall f\in\Phi^F,\forall t\in T \tag{1l}$$

$$v_k(t)+y_k(t)=1\ \forall k\in\Phi^K,\forall t\in T \tag{1m}$$

$$0\le p_k^{disc}(t)\le v_k(t)\overline{P}^{dis}\ \forall k\in\Phi^K,\forall t\in T \tag{1n}$$

$$0\le p_k^{ch}(t)\le y_k(t)\overline{P}_k^{ch}\ \forall k\in\Phi^K,\forall t\in T \tag{1o}$$

$$e_k(t)=e_k(t-1)-\left(\frac{p_k^{disc}(t)}{\eta_k^{dis}}\right)+\left(p_k^{ch}(t)\times\eta_k^{ch}\right)-\left(e_j(t)\times\eta_k^{loss}\right)\ \forall k\in\Phi^K,\forall t\in T \tag{1p}$$

$$v_k(t)\in\{0,1\},y_k(t)\in\{0,1\}\ \ \forall k\in\Phi^K,\forall t\in T \tag{1q}$$

$$\sum_{f\in\Lambda_z^F}p_f(t)+\sum_{w\in\Lambda_z^W}p_w(t)+\sum_{s\in\Lambda_z^S}p_s(t)+\sum_{k\in\Lambda_z^K}p_k^{disc}(t)-\sum_{k\in\Lambda_z^K}p_j^{ch}(t)-\sum_{nz\in\Lambda_z^{NZ}}P_{z,nz}^{exp}(t)+\sum_{nz\in\Lambda_z^{NZ}}P_{nz,z}^{imp}(t)-\overline{L}_z(t)= F_{z,nz}(t)\ \forall z\in\Phi^Z,\forall t\in T \tag{1r}$$

$$F_{z,nz}(t)\le\overline{P}_{z,nz}^F\ \forall z\in Z,\ \forall nz\in\Lambda_z^{NZ},\forall t\in T \tag{1s}$$

$$F_{z,nz}(t)\ge-\overline{P}_{z,nz}^F\ \ \forall z\in Z,\ \forall nz\in\Lambda_z^{NZ},\forall t\in T \tag{1t}$$

2.1.3 Economic Dispatch

Equations (2a) through (2d) represent the formulation used for calculating the locational marginal prices for energy. This model is a relaxed version of the unit commitment model from the previous section in which binary commitment, startup, and shutdown variables $\left(x_f(t),\ u_f(t),\ d_f(t),\ v_k(t) \text{ and } y_k(t)\right)$, are set to their welfare-maximizing schedules, $\left(x_f^*(t),\ u_f^*(t),\ d_f^*(t),\ v_k^*(t) \text{ and } y_k^*(t)\right)$, serving now as constraints represented by Equations (2b) and (2c). The relaxation results in a linear model whose dual variables yield the market-clearing prices for energy in each zone z, $\pi_{Z,t}^{LMP}$, while balancing the energy demand and supply, as outlined by Equation (2d).

$$\underset{P_{ft}, P_{nt}, P_{st}, P_{wt}, P_{ft}, p_{kt}^{ch}, p_{kt}^{disc}, e_{kt}, f_{z,zn,t}}{\text{Min}} \sum_{t \in \Phi^T} \sum_{f \in \Phi^F} \left(V_f^C(t) \times p_f(t) + N_f^C(t) \times x_f(t) + S_f^C(t) \times u_f(t)\right) \tag{2a}$$

Subject to constraints (1b) through (1h), (1n) through (1p), (1s) through (1t), and

$$x_f(t) = x_f^*(t),\ u_f(t) = u_f^*(t),\ d_f(t) = d_f^*(t) \tag{2b}$$

$$v_f(t) = v_k^*(t),\ y_f(t) = y_k^*(t) \tag{2c}$$

$$\begin{aligned} &\textstyle\sum_{f \in \Lambda_z^F} p_f(t) + \sum_{w \in \Lambda_z^w} p_w(t) + \sum_{s \in \Lambda_z^s} p_s(t) + \sum_{k \in \Lambda_z^k} p_k^{disc}(t) - \sum_{k \in \Lambda_z^k} p_j^{ch}(t) - \sum_{nz \in \Lambda_z^{NZ}} P_{z,nz}^{exp}(t) \\ &+ \textstyle\sum_{nz \in \Lambda_z^{NZ}} P_{nz,z}^{imp}(t) - \overline{L}_z(t) = F_{z,nz}(t) : \pi_{z,t}^{LMP} \quad \forall z \in \Phi^Z, \forall t \in T \end{aligned} \tag{2d}$$

2.1.4 Uplift Payment Calculation

Equation (3a) calculates the make-whole payment given the electricity production, startup, and shutdown schedules $x_f^*(t)$, $u_f^*(t)$, and $d_f^*(t)$; the generators' costs; and zonal marginal prices $\pi_{Z,t}^{LMP}$. Here, the daily costs and revenues of all generators are calculated and compared. Resources that follow the transmission operator's dispatch instructions and realize a negative profit on the day receive make-whole payments such that their total in market revenues and MWP become equal to their total daily operation costs.

$$MWP_g^T = -\text{Min}\left\{0, \sum_{t \in \Phi^T} \left(\pi_{Z,t}^{LMP} \times p_{f,t}^* - V_f^C(t) \times p_f^*(t) + N_f^C(t) \times x_f^*(t) + S_f^*(t) \times u_f^*(t)\right)\right\} \tag{3a}$$

2.2 Data

To initialize our model, we gathered detailed data on the demand for electricity in PJM, the set of generators deployed in PJM, fuel costs associated with these generators, renewables generation in PJM's footprint, energy storage assets, transmission constraints present between modeled PJM zones, imports/exports between PJM and external grid systems, and imports/exports between states within PJM. A full accounting of these data is documented in Appendix A.

RESULTS

3.1 EMST Performance

Because we are modeling plants known to be in the PJM footprint with known performance characteristics, the closer the simulated prices and generation mix to the actual prices and generation mix, the more confident we can be in the results of our model during counterfactual scenarios.

In Table 1, we present descriptive statistics comparing the observed prices in PJM during 2019 to the prices simulated by EMST over the same period. We see that our simulation is well-centered but does not fully capture the wider variation present in the observed prices.

Table 1. Descriptive statistics of PJM-wide prices in 2019

Time Series	# of Obs.	Mean, $/MWh	Std. Deviation, $/MWh	Median, $/MWh	Min., $/MWh	Max., $/MWh	Skewness	Kurtosis
Observed	8,760	25.99	9.26	24.36	8.8	160.36	3	20.74
EMST	8,760	26.43	4.94	26.05	14.23	55.67	0.96	2.03

We also calculate a Pearson's product-moment correlation, Spearman's ρ rank correlation coefficient, and Kendall's τ rank correlation coefficient.[5] Our correlation analysis is shown in Table 2. All three tests reject, with more than 95% confidence, the null hypothesis of zero correlation between the observed prices and the time series of prices simulated by EMST.

Table 2. Correlation between observed and EMST prices in 2019

Time Series	Obs.	Pearson's Product-Moment Correlation	Spearman's ρ	Kendall's τ
Full Year (2019)	8,760	0.66	0.67	0.48

Finally, we compare the generation mix that was observed in PJM in 2019 to the generation mix simulated by EMST. These data are shown in Table 3. We note a few key differences in the observed utilization of power generators compared to our simulated results. First, our simulations show more electricity generation from nuclear assets. This is because EMST assumes that nuclear generators operate at full load for all hours of 2019 and does not account for turndowns. Second, Table 3 shows that EMST dispatches more electricity from natural gas units and less from coal units compared to 2019 observations. Our model selects the lowest cost asset, often a natural gas combined-cycle unit, and although it ensures that operational reliability requirements are met, it does not consider broader grid security and reliability concerns. In reality, PJM will consider these factors and sometimes dispatch out-of-merit-order units, like more expensive coal, on a "must-run" basis, effectively trading lower costs for improved grid reliability. We do not have sufficient data to include must-run requirements and so our simulation does not address these instances. Last, our simulated renewables mix—especially that of wind—is higher than the observed renewable mix. In practice, PJM will sometimes curtail renewable assets because of transmission congestion. EMST does not capture these choices either, instead modeling full production from these resources in all hours of the year.

[5] We note that conducting a rank correlation may be preferable to a Pearson's product-moment because rank correlations are robust to nonnormally distributed time series (Kowalski 1972).

Table 3. Actual versus simulated generation mix in PJM in 2019

Fuel Type	Percent of Observed Mix	Percent of Simulated Mix
Coal	23.72%	17.73%
Gas	36.08%	38.70%
Hydro	1.99%	2.19%
Nuclear	33.64%	37.80%
Oil and other fuels	1.38%	0.07%
Solar	0.29%	0.36%
Wind	2.90%	3.17%

In sum, though, we argue that the discrepancy present between observed and simulated prices and generation mixes are the result of the model being unable to capture shocks that create real-world must-run requirements and/or price spikes. Because of limitations in available data between transmission zones, EMST divides PJM into nine transmission regions, depicted in Figure 2. EMST transmission zones in PJM. This contrasts with the PJM-published transmission zones shown in Figure 3. PJM transmission zones (PJM 2021a). The coarseness of the EMST transmission topography relative to the true grid topography dampens the impact of exogeneous shocks like unplanned outages or anomalous weather events. The model projects a broader fleet of available generators in each simulated transmission zone, providing an artificial backstop to supply shocks that are not manifest in the actual system. That the simulation does not fully capture some extreme exogeneous effects yet still has well-centered prices, strong correlation, and accurate generation mixes when compared to observed data, speaks to the general quality of the simulation for the purposes of this paper—namely, to assess the changes in market participation on overall system performance (rather than predicting specific shocks and corresponding price events).

We conclude, then, that EMST provides a reliable avenue through which to estimate profits to generating assets, the average cost to serve load, and the emissions intensity of the dispatched system and will use these simulated results to analyze coalition stability. For a deeper discussion on EMST's fidelity, see Appendix B.

Figure 2. EMST transmission zones in PJM

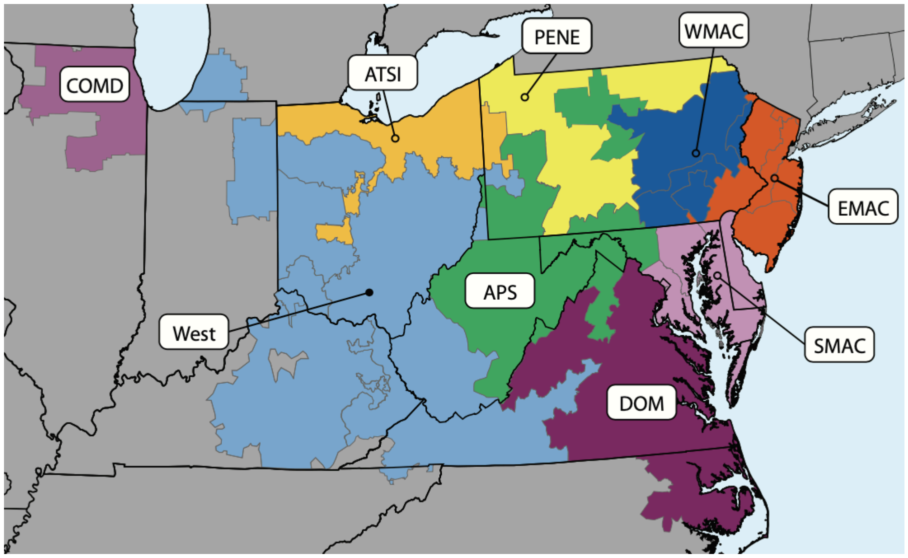
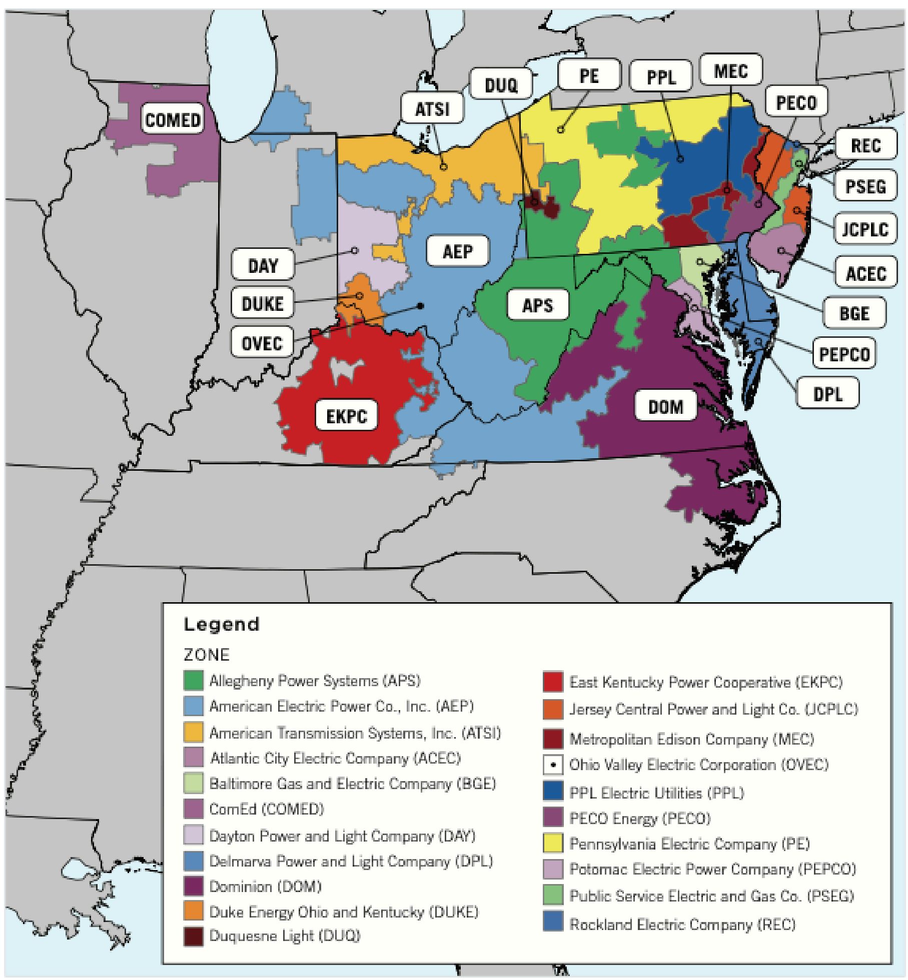


Figure 3. PJM transmission zones (PJM 2021a)



3.2 PJM Base Case

Tables 4, 5, and 6 present the key results of the base case in 2019, where every state participates in the PJM's wholesale energy market. Table 4 depicts the generation mix of each state as well as that state's total generation (MWh) that was dispatched by EMST. The aggregated production shown in Table 4 is built by the hourly dispatch outcomes of the simulation. Combined with hourly prices and the cost to generate this electricity, we build Table 5, which shows profits to each generator type in each state.

It is interesting to note the different profits to renewable assets. Solar, wind, and hydro generators are all modeled in EMST as having zero marginal costs. Yet, the profits, in $/MWh, differ for these assets not only across states but also within states. This is because their revenue is dependent on the hours that they are producing and the market clearing price in those given hours, an important consideration for intermittent resources such as these.

While Table 5 captures a measure of welfare to suppliers in each state, Table 6 offers additional data from our simulation, including the average cost to serve load and annual CO_2 emissions, two factors that will contribute to the overall welfare of the state.[6] Here, the average cost to serve load is the price that in-state retailers pay to the wholesale generators so they can meet consumer demand and the annual CO_2 emissions are the total tons of carbon emitted by in-state generators over the course of 2019. Our simulated results meet our expectations. We see, for instance, that annual emissions are highest in states with the highest generation, drawing a connection between the production quantities in Table 4 and climate impacts.

Of course, the base case results have standalone interest, but the real contribution of this work is to understand how states are impacted by the defection of another in the consortium. We offer those results in the next section.

Table 4. Generation mix for each state in the base base

State	Solar Power Generation, %	Wind Power Generation, %	Hydro Power Generation, %	Coal Power Generation, %	Natural Gas Power Generation, %	Nuclear Power Generation, %	Oil Power Generation, %	Total State Electricity Generation, MWh
DC	9.171	-	-	-	90.829	-	-	54,343
DE	0.902	0.096	-	1.037	97.848	-	0.117	3,366,672
IL	0.015	8.575	0.063	18.191	9.221	63.936	-	143,879,136
IN	0.089	19.845	0.235	35.630	44.201	-	-	29,229,172
KY	0.201	-	13.163	75.147	11.488	-	-	7,090,584
MD	0.905	1.033	10.905	18.422	20.191	48.541	0.003	30,820,009
MI	0.009	-	0.391	-	30.717	68.883	-	27,685,361
NC	34.230	10.357	34.833	20.580	-	-	-	2,960,723
NJ	1.053	0.022	0.065	0.104	50.042	48.698	0.018	62,368,010
OH	0.048	1.843	0.528	28.183	53.025	15.953	0.421	117,181,608
PA	0.018	0.781	2.064	13.299	53.288	30.550	-	260,738,578
TN	-	-	-	68.236	31.764	-	-	1,685,533
VA	1.172	-	4.729	2.576	26.964	64.559	-	48,413,776
WV	-	4.597	12.349	74.115	8.939	-	-	21,219,214

[6] A richer discussion on this topic is reserved for Section 3.4, Welfare Calculations.

Table 5. Profits to generation types in the base case

State	Solar Profits, $/MWh[a]	Wind Profits, $/MWh[a]	Hydro Profits, $/MWh	Coal Profits, $/MWh	Natural Gas Profits, $/MWh	Nuclear Profits, $/MWh	Oil Profits, $/MWh	Average Profits to All Generators, $/MWh
DC	$27.939	-	-	-	$1.321	-	-	$3.762
DE	$27.625	$26.587	-	$11.823	$4.931	-	$0.00	$5.222
IL	$25.962	$23.620	$26.524	$2.191	$1.661	$14.748	-	$12.027
IN	$27.902	$27.110	$29.061	$0.941	$2.578	-	-	$6.948
KY	$25.610	-	$24.482	$1.079	$0.086	-	-	$4.095
MD	$27.778	$27.268	$28.975	$21.360	$1.641	$17.072	$0.00	$16.246
MI	$27.902	-	$29.061	-	$3.066	$17.067	-	$12.814
NC	$27.874	$27.386	$29.070	$5.285	-	-	-	$23.591
NJ	$27.625	$26.587	$29.030	$7.366	$4.879	$14.692	$0.082	$9.920
OH	$27.902	$27.110	$29.061	$0.780	$3.767	$17.067	$8.690	$5.643
PA	$25.132	$24.560	$25.092	$0.859	$2.604	$14.352	-	$6.600
TN	-	-	-	$9.792	$6.222	-	-	$8.658
VA	$27.825	-	$29.065	$3.317	$2.095	$17.072	-	$3.372
WV	-	$27.330	$29.061	$1.186	$2.741	-	-	$5.969

[a] Solar and wind profits do not include subsidies or other renewable credits.

Table 6. More results from the base case

State	Demand, MWh	Average Cost to Serve Load, $/MWh	Annual CO_2 Emissions from Generation, tons	Net Exports (+) or Net Imports (-) from PJM, MWh
DC	8,772,540	$27.755	9,696	-8,718,198
DE	12,133,001	$27.748	2,352,029	-8,766,328
IL	96,511,187	$25.441	38,408,952	47,367,949
IN	21,194,371	$27.608	16,065,906	8,034,801
KY	25,082,353	$25.929	5,585,576	-17,991,769
MD	66,892,050	$27.827	9,774,654	-36,072,041
MI	5,864,708	$27.608	3,472,462	21,820,652
NC	3,565,230	$27.775	15,649	-604,507
NJ	76,910,073	$27.579	13,145,484	-14,542,063
OH	155,915,008	$27.704	62,074,508	-38,733,399
PA	155,018,292	$25.949	95,672,023	105,720,286
TN	4,214,924	$27.805	744,770	-2,529,391
VA	123,462,023	$27.780	6,319,909	-75,048,248
WV	31,670,684	$27.803	16,950,714	-10,451,470

3.3 Effect of State Defections on Other States' Electricity Industry

We model the defection of five different states from the wholesale energy markets in PJM. New Jersey and Maryland were chosen for threats they have made to leave PJM's capacity market in response to a change in market rules that would have made state renewable energy targets more difficult to achieve (Morehouse 2020; Walton 2020).[7] The defection we model of exiting the wholesale electricity market altogether is beyond the threats currently made by these states to exit the capacity market, but it is not out of the realm of possibility that states could broaden their market defection. Importantly, this modeling allows us to evaluate the effects states have on other states in a coalition and allows us to extend the analysis already conducted by the market monitor regarding New Jersey and Maryland exiting the capacity market (Monitoring Analytics 2020a, 2020b). We selected Virginia as another potential defector because it is the largest importer of electricity in PJM and, similarly, we selected Pennsylvania and Illinois because they are the largest and second largest exporters of electricity within the RTO, respectively. Our simulations did not include analysis of the outcomes in the defecting state.

Table 7. Total generation after a state defection

State	Demand, MWh[a]	Net Exports (+) or Net Imports (-) from PJM, MWh[b]	Total Generation, MWh	Percent Change in Total Generation Compared to Base Case Simulation[c]				
			Base Case	NJ Exit	MD Exit	VA Exit	PA Exit	IL Exit
DC	8,772,540	-8,718,198	54,343	-0.76%	-8.82%	-19.17%	96.46%	12.83%
DE	12,133,001	-8,766,328	3,366,672	-3.15%	-15.50%	-15.14%	88.04%	4.72%
IL	96,511,187	47,367,949	143,879,136	-0.09%	-1.37%	-3.68%	0.87%	N/A
IN	21,194,371	8,034,801	29,229,172	-1.73%	-14.34%	-30.42%	14.43%	18.63%
KY	25,082,353	-17,991,769	7,090,584	-2.88%	-5.74%	-12.65%	59.97%	5.51%
MD	66,892,050	-36,072,041	30,820,009	0.15%	N/A	-9.17%	25.26%	7.78%
MI	5,864,708	21,820,652	27,685,361	-0.39%	-2.40%	-6.42%	2.78%	2.78%
NC	3,565,230	-604,507	2,960,723	-0.21%	-0.85%	-2.58%	1.31%	0.99%
NJ	76,910,073	-14,542,063	62,368,010	N/A	-6.89%	-9.68%	31.21%	1.67%
OH	155,915,008	-38,733,399	117,181,608	-0.74%	-10.37%	-21.48%	10.41%	13.85%
PA	155,018,292	105,720,286	260,738,578	-0.84%	-2.02%	-5.59%	N/A	2.26%
TN	4,214,924	-2,529,391	1,685,533	0.01%	-1.16%	-3.86%	0.98%	0.84%
VA	123,462,023	-75,048,248	48,413,776	-0.21%	-6.98%	N/A	15.32%	11.01%
WV	31,670,684	-10,451,470	21,219,214	-8.43%	-30.61%	-52.69%	45.55%	45.03%

[a] Demand figures are for the base case and are assumed to be unchanged under defection.
[b] Net exports/imports are for the base case and are calculated as Total Generation—Demand.
[c] The change in total generation is not modeled for the defecting state.

Table 7 depicts the results of a state defection on the total production of electricity by each state. The Base Case is shown, and the effects of a defection are captured in the "percent change" columns for each relevant defection. Negative percent changes are colored red. As major suppliers of electricity to

[7] A capacity market is intended to ensure resource adequacy to meet peak load demand at any time throughout the year. PJM specifies the demand for capacity three years out and bidders offer to ensure their capacity is available at that time at a given price per MW (technically a $/MW-month offer). These capacity payments accrue to the bidders and are paid by the customers of the utilities serving load in PJM. Withdrawing from the capacity market means that resource adequacy requirements must be met by other means. They cannot be simply ignored by the utilities in the state defecting from the capacity market.

the entire system, when Pennsylvania or Illinois defect, all states are called upon to make up the supply shortage. Generation changes post-defection can be dramatic: if Pennsylvania leaves, for example, New Jersey and Ohio end up carrying 45% of the supply deficit (on a MWh basis).

The opposite effect holds when the largest importer, Virginia, leaves PJM. With heavy demand lifted from the system, states everywhere reduce their generation. Interesting, again, is the effect on Ohio. Even though Ohio does not share a border with Virginia, Ohio would need to reduce generation by over 20% under a Virginia-defection scenario, reflecting the long reach of spillover effects in large transmission systems.

With the two heavy exporters and one heavy importer marking the bounds, the effects created by New Jersey or Maryland choosing to exit PJM's wholesale market fall within those margins. Maryland, being a larger importer than New Jersey, creates unambiguous effects to total generation that fall in line—but of lesser scale—with a Virginia defection. Interesting, though, is the impact a New Jersey defection has on total generation. In this scenario, most states reduce output as expected, but Maryland and Tennessee slightly increase production, albeit by a very small amount.

Table 8. Annual CO_2 emissions after a state defection

State	Demand, MWh[a]	Net Exports (+) or Net Imports (-), MWh[b]	CO_2 Emissions, tons	Percent Change in Annual CO_2 Emissions Compared to Base Case Simulation[c]				
			Base Case	NJ Exit	MD Exit	VA Exit	PA Exit	IL Exit
DC	8,772,540.0	-8,718,197.5	9,696	-0.85%	-27.74%	-42.08%	41.06%	44.04%
DE	12,133,000.7	-8,766,328.3	2,352,029	-36.60%	-44.10%	-9.92%	23.62%	3.34%
IL	96,511,187.3	47,367,948.8	38,408,952	-0.18%	-3.94%	-10.30%	3.06%	N/A
IN	21,194,371.2	8,034,800.9	16,065,906	-2.58%	-21.47%	-42.49%	21.87%	28.25%
KY	25,082,353.2	-17,991,769.2	5,585,576	-3.40%	-5.70%	-13.32%	78.10%	4.72%
MD	66,892,049.9	-36,072,041.1	9,774,654	0.16%	N/A	-12.76%	36.34%	11.24%
MI	5,864,708.3	21,820,652.4	3,472,462	-1.27%	-7.79%	-20.26%	9.01%	9.01%
NC	3,565,229.9	-604,507.4	15,649	-1.04%	-4.13%	-12.52%	6.37%	4.81%
NJ	76,910,072.7	-14,542,062.8	13,145,484	N/A	-14.52%	-19.18%	66.31%	3.53%
OH	155,915,007.5	-38,733,399.3	62,074,508	-1.32%	-17.96%	-34.85%	18.76%	24.73%
PA	155,018,291.6	105,720,286.3	95,672,023	-1.30%	-4.41%	-11.97%	N/A	5.48%
TN	4,214,923.8	-2,529,390.9	744,770	0.01%	-1.16%	-3.86%	0.98%	0.84%
VA	123,462,023.3	-75,048,247.7	6,319,909	-0.65%	-24.28%	N/A	54.95%	39.41%
WV	31,670,684.1	-10,451,470.3	16,950,714	-10.96%	-38.37%	-66.04%	57.34%	56.90%

[a] Demand figures are for the base base and are assumed to be unchanged under defection.
[b] Net exports/imports are for the base case and are calculated as Total Generation—Demand.
[c] The change in the annual CO_2 emissions is not modeled for the defecting state.

We offer another lens into these defection effects with Table 9 Average cost to serve load after a state defection, where we report the annual CO_2 emissions under different scenarios. For readability, we color the text red for negative percent changes in CO_2 emissions. The results of Table 9. Average cost to serve load after a state defection are closely tied to our total generation results from Table 7. In all cases, if a state decreases total generation after a state defection, then the amount of CO_2 that is emitted by in-state power generation sources also decreases. The interesting comparison is in the magnitude of these changes. When any of the net importers defects, Ohio reduces its total generation less than the amount that CO_2 emissions drops. That is, more CO_2 intensive generators in Ohio are falling out of the merit order post-defection. But the opposite occurs when a net exporter defects. Under Pennsylvania and Illinois defection scenarios, Ohio increases its supply by 10.41% and 13.85%, respectively, while CO_2 emissions jump by 18.76% and 24.73%. Indeed, the fleet of plants that are on the margin throughout the year produce more CO_2 per MWh than the inframarginal plants. By evaluating the CO_2 emissions before and after different defection scenarios, we get a sense of the impacts that one state's actions can have not only on another state's production, but also on any climate initiatives. We return to this concept of climate spillovers in the next section.

In Table 9 we report the impact of defection on the average cost to serve load. A negative percent change is represented by red text. We define the average cost to serve load as the sum of each hour's in-state demand multiplied by the clearing price of the wholesale market in that given hour. This measure is, essentially, the cost that the retailers would incur to buy power from the wholesale electricity market before marking it up and selling it to consumers. The value represents our proxy for consumer welfare with higher values generally equating to larger charges on electricity bills across the state. We return to this concept in Section 3.4, Welfare Calculations.

Table 9. Average cost to serve load after a state defection

State	Demand, MWh[a]	Net Exports (+) or Net Imports (-) from PJM, MWh[b]	Average Cost to Serve Load, $/MWh	Percent Change in Average Cost to Serve Load Compared to Base Case Simulation[c]				
			Base Case	NJ Exit	MD Exit	VA Exit	PA Exit	IL Exit
DC	8,772,540	-8,718,198	$27.755	-0.52%	-4.28%	-10.12%	7.26%	4.75%
DE	12,133,001	-8,766,328	$27.748	-4.53%	-3.95%	-4.53%	8.04%	1.13%
IL	96,511,187	47,367,949	$25.441	-0.52%	-2.23%	-6.39%	-0.03%	N/A
IN	21,194,371	8,034,801	$27.608	-0.48%	-4.19%	-10.14%	1.76%	4.72%
KY	25,082,353	-17,991,769	$25.929	-0.16%	-2.60%	-6.31%	12.48%	2.98%
MD	66,892,050	-36,072,041	$27.827	-0.88%	N/A	-9.64%	7.38%	4.42%
MI	5,864,708	21,820,652	$27.608	-0.48%	-4.19%	-10.14%	1.76%	4.72%
NC	3,565,230	-604,507	$27.775	-0.53%	-4.28%	-10.21%	6.78%	4.75%
NJ	76,910,073	-14,542,063	$27.579	N/A	-3.99%	-4.52%	7.68%	1.08%
OH	155,915,008	-38,733,399	$27.704	-0.49%	-4.20%	-10.12%	1.70%	4.73%
PA	155,018,292	105,720,286	$25.949	-1.23%	-2.62%	-5.02%	N/A	2.13%
TN	4,214,924	-2,529,391	$27.805	-0.50%	-4.24%	-10.27%	1.63%	4.74%
VA	123,462,023	-75,048,248	$27.780	-0.54%	-4.27%	N/A	5.99%	4.73%
WV	31,670,684	-10,451,470	$27.803	-0.49%	-4.23%	-10.24%	4.19%	4.73%

[a] Demand figures are for the base case and are assumed to be unchanged under defection.
[b] Net exports/imports are for the base case and are calculated as Total Generation—Demand.
[c] The change in average cost to serve load is not modeled for the defecting state.

The insight of Table 9 is intertwined with the balance of supply and demand for the PJM system. Under the base case, the average cost to serve load reflects the co-optimization of the whole system. If a net exporter exits, it takes with it a larger volume of supply than demand and the newly equilibrated system must clear with more expensive units than the base case. Thus, the average cost to serve load increases.[8]

[8] This generally holds for all states that remain after a net exporter exits, with one exception. When Pennsylvania defects, the average cost to serve load in Illinois decreases. We note, though, that the magnitude of this change is miniscule.

By contrast, if a net importer exits, then demand across the system drops more than the supply lost by the defecting state. The most expensive generators (not all of them being singularly located in the exiting state) can fall out of the merit order and the average cost to serve load unambiguously decreases for all states that remain in PJM.

Table 7 and Table 9 demonstrate the effects of co-optimization and the long reach of an interconnected consortium and Table 9. Average cost to serve load after a state defection summarizes the emissions intensity of each state's generation fleet that is dispatched throughout the year.

Finally, in Table 10 we present generation profits as a proxy for supplier welfare. The consequences of defection on generation profits suggests heterogeneous impacts likely tied to generation mix across states. Here, we need to recognize that like-generators have like-costs, implying that similar types of generators in a state's fleet will cluster around different marginal cost levels. In other words, the different coal generators in a state—even those that were built in different time periods—will typically have similar marginal cost levels. The same can be said for the natural gas combined cycle fleet, the natural gas simple cycle fleet, and other technologies. A supply curve can be constructed, then, ordering lowest cost generators to highest cost and we will generally observe clumping of technologies along the supply axis. When demand shifts after a state defection, co-optimization under the new system might shift in-state generator merit order to include or exclude these fuel/technology clusters, impacting the overall profitability to suppliers. So, while a net importer or net exporter defecting unambiguously affects total generation, total CO_2 emissions, and average cost to serve load, how these defections impact supplier profits is less apparent on the surface and depends on in-state generation dynamics.

Table 10. Generation profits after a state defection

State	Demand, MWh[a]	Net Exports (+) or Net Imports (-), MWh[b]	Generation Profits, $/MWh	Percent Change in Generation Profits Compared to Base Case Simulation[c]				
			Base Case	NJ Exit	MD Exit	VA Exit	PA Exit	IL Exit
DC	8,772,540	-8,718,198	$3.762	4.97%	2.45%	4.42%	-0.83%	3.55%
DE	12,133,001	-8,766,328	$5.222	-42.58%	-20.72%	-7.50%	-49.26%	3.19%
IL	96,511,187	47,367,949	$12.027	-0.79%	-2.76%	-7.92%	-0.81%	N/A
IN	21,194,371	8,034,801	$6.948	0.01%	4.39%	11.69%	-8.57%	-2.72%
KY	25,082,353	-17,991,769	$4.095	2.24%	2.24%	7.07%	41.96%	0.25%
MD	66,892,050	-36,072,041	$16.246	-1.81%	N/A	-4.90%	-9.86%	-0.73%
MI	5,864,708	21,820,652	$12.814	-0.64%	-6.12%	-13.94%	1.24%	6.99%
NC	3,565,230	-604,507	$23.591	-0.47%	-4.25%	-9.86%	6.13%	4.55%
NJ	76,910,073	-14,542,063	$9.920	N/A	-3.20%	-0.47%	-4.98%	1.22%
OH	155,915,008	-38,733,399	$5.643	-1.19%	-4.26%	-13.05%	-3.59%	4.24%
PA	155,018,292	105,720,286	$6.600	0.64%	-3.17%	-6.50%	N/A	3.79%
TN	4,214,924	-2,529,391	$8.658	-1.36%	-12.04%	-27.93%	5.44%	14.26%
VA	123,462,023	-75,048,248	$13.372	-0.80%	-1.07%	N/A	-2.72%	-1.01%
WV	31,670,684	-10,451,470	$5.969	6.46%	26.48%	60.67%	-13.15%	-17.38%

[a] Demand figures are for the base case and are assumed to be unchanged under defection.
[b] Net exports/imports are for the base case and are calculated as Total Generation—Demand.
[c] The change in generation profits is not modeled for the defecting state.

3.4 Welfare Calculations

Our total welfare calculations follow from the findings presented in Section 3.3, Effect of State Defections on Other States' Electricity Industry. Producer surplus is easily determined by multiplying the average profit per MWh of generation by the total generation for each state in each simulated scenario. These results are shown in Table 11. Percent changes colored green indicate that producer surplus has increased while percent changes colored red reflect a reduction in producer surplus in that state. The calculation of producer surplus in exit scenarios factors both the change in average profit per MWh and the change in total generation in the state.

We can gain insight from changes in producer surplus. Broadly speaking, the trend of Table 11 suggests that if a net importer exits the PJM energy market, then producer surplus in the remaining states decreases; the opposite effect is found when a net exporter exits the PJM energy market.

There are two exceptions to this rule: Washington, DC, and Delaware. Consider Delaware, for example, and observe that producer surplus decreases by 4.59% when Pennsylvania exits from the energy market. When such a large net exporter is removed from the system, this supply needs to be made up by other states, including Delaware. Indeed, we see from Table 7 that a Pennsylvania defection increases generation in Delaware by 88.04%. Yet, Table 10 shows per-MWh profitability of Delaware generation is reduced by 49.26% under the same scenario. The drop in average profitability dominates the increase in generation. A similar argument can be made with Washington, DC, where, when New Jersey defects, the increased profitability of generators dominates the drop in production.

Table 11. Producer surplus for each state under different simulations

State	Producer Surplus, $	Percent Change in Producer Surplus Compared to Base Case Simulation[a]				
	Base Case	NJ Exit	MD Exit	VA Exit	PA Exit	IL Exit
DC	204,448	4.17%	-6.59%	-15.60%	94.84%	16.84%
DE	17,582,294	-44.39%	-33.01%	-21.50%	-4.59%	8.06%
IL	1,730,433,535	-0.88%	-4.09%	-11.31%	0.06%	N/A
IN	203,084,173	-1.73%	-10.58%	-22.28%	4.63%	15.41%
KY	29,033,448	-0.71%	-3.62%	-6.47%	127.09%	5.77%
MD	500,707,376	-1.66%	N/A	-13.63%	12.92%	7.00%
MI	354,759,876	-1.03%	-8.37%	-19.47%	4.06%	9.97%
NC	69,846,394	-0.69%	-5.06%	-12.19%	7.52%	5.58%
NJ	618,661,033	N/A	-9.87%	-10.10%	24.68%	2.91%
OH	661,264,989	-1.92%	-14.18%	-31.73%	6.45%	18.67%
PA	1,720,955,038	-0.20%	-5.13%	-11.73%	N/A	6.14%
TN	14,593,773	-1.35%	-13.06%	-30.71%	6.47%	15.22%
VA	647,413,157	-1.01%	-7.97%	N/A	12.18%	9.89%
WV	126,666,334	-2.52%	-12.23%	-23.99%	26.41%	19.83%

[a] The change in producer surplus is not modeled for the defecting state.

We also make a proxy calculation for consumer surplus using wholesale energy receipts. The true consumer surplus would require a willingness-to-pay measure for electricity by individuals in each state.

Because we are primarily interested in directional effects, we argue that the payments made to wholesale generation are a sufficient measure for capturing changes in consumer surplus under different defection scenarios. Our measure, consumer wholesale costs, has a negative effect on true consumer surplus. That is, if we find that our consumer wholesale costs increase, then we infer a decrease in true consumer surplus. To calculate this value, we multiply the average cost to serve load by the total demand of the state. This is the amount of money that would be conveyed to retailers to provide utility services to electricity consumers.

The literature suggests our approach for understanding changes in true consumer surplus are viable. First, electricity consumers are relatively unresponsive to marginal price fluctuations (Borenstein 2009; Borenstein and Bushnell 2018; Shin 1985). Rather, Ito (2014) found evidence that consumption decisions are more influenced by the average cost of delivered electricity that consumers face. Furthermore, Zhu et al. (2018) determined that, as with most goods, the long-run demand for residential electricity was more elastic than short-run demand. We argue, then, that consumers would measure their welfare based on the average cost they are paying for electricity and would, in the short run, maintain their current consumption even under average price changes on their electric utility bill. In sum, decreased average price levels will have salience to consumers and reflect an increase in consumer welfare.

We are left, then, with determining how retailers may or may not change their pricing behavior based on changes to the wholesale pricing. Here again the literature suggests that fluctuations in the marginal costs of producers are often absorbed by the retailers (Davis and Muehlegger 2010; Friedman 1991; Puller and West 2013). That is, retail suppliers will likely not pass-through high-frequency marginal cost fluctuations. Instead, we claim that changes in levels (i.e., average cost) will trigger pricing adjustments.

Therefore, under a state defection, if the retailers in a state that remains in the coalition faces lower average costs of supply, we would expect that the lower average cost would trigger an adjustment to retail utility bills downward. Consumers would not adjust their consumption profile in the near term, consuming the same amount of electricity for a lower retail price of electricity, improving their welfare. By contrast, consumer welfare would decrease analogously with an increase in the average cost of supply, following the same logic that higher average costs paid by retailers to generating assets would translate to higher average retail prices paid by the consumer.

In Table 12 we show how different state defections impact consumer wholesale costs. Percentages colored green represent decreases in consumer wholesale costs which mean increases in true consumer surplus. Percentages colored red depict the opposite effect. The results are unambiguous and as expected: when a net-importing state leaves the PJM energy market, consumers in the remaining states are better off because of the lower retail prices of electricity that result. Upon defection, the net importer no longer burdens supply in the states that stay in the consortium, reducing total payments to the remaining generation fleet.

Table 12. Consumer wholesale costs for each state under different simulations

State	Consumer Wholesale Costs, $	Percent Change in Consumer Wholesale Costs Compared to Base Case Simulation[a]				
	Base Case	NJ Exit	MD Exit	VA Exit	PA Exit	IL Exit
DC	243,485,679	-0.52%	-4.28%	-10.12%	7.26%	4.75%
DE	336,662,966	-4.53%	-3.95%	-4.53%	8.04%	1.13%
IL	2,455,339,123	-0.52%	-2.23%	-6.39%	-0.03%	N/A

State	Consumer Wholesale Costs, $	Percent Change in Consumer Wholesale Costs Compared to Base Case Simulation[a]				
	Base Case	NJ Exit	MD Exit	VA Exit	PA Exit	IL Exit
IN	585,143,593	-0.48%	-4.19%	-10.14%	1.76%	4.72%
KY	650,365,982	-0.16%	-2.60%	-6.31%	12.48%	2.98%
MD	1,861,374,783	-0.88%	N/A	-9.64%	7.38%	4.42%
MI	161,915,465	-0.48%	-4.19%	-10.14%	1.76%	4.72%
NC	99,023,390	-0.53%	-4.28%	-10.21%	6.78%	4.75%
NJ	2,121,117,550	N/A	-3.99%	-4.52%	7.68%	1.08%
OH	4,319,477,984	-0.49%	-4.20%	-10.12%	1.70%	4.73%
PA	4,022,593,145	-1.23%	-2.62%	-5.02%	N/A	2.13%
TN	117,197,373	-0.50%	-4.24%	-10.27%	1.63%	4.74%
VA	3,429,827,551	-0.54%	-4.27%	N/A	5.99%	4.73%
WV	880,553,245	-0.49%	-4.23%	-10.24%	4.19%	4.73%

[a] The change in consumer wholesale costs is not modeled for the defecting state.

Comparing the results presented in Table 11 and Table 12 illustrates the tradeoffs made by states between producers and consumers. For nearly all states in all scenarios, what is good for producers is bad for consumers and vice versa. Whether a state is better or worse off because of a defection is a broader welfare question that must include some equity considerations. Our simulations predict two distinct exceptions to this producer/consumer tradeoff: Delaware is unambiguously worse off if Pennsylvania defects (both producers and consumers lose), and Washington, DC, is unambiguously better off if New Jersey defects (both producers and consumers gain).[9]

For all other states in all other scenarios, our evaluation of total welfare to remaining states after a defection must account for the typical tradeoffs between producers and consumers. We believe this is a distinctly political question with, likely, a political answer. While beyond the scope of this paper, we foresee a total welfare calculation taking the form

$$W_{i,k} = (1 - \lambda_i) PS_{i,k} + \lambda_i v_i CS_{i,k} \tag{4}$$

where $W_{i,k}$ is the welfare in state i under simulation scenario k, PS is our measure of producer surplus, CS is our proxy measure for consumer surplus, v_i is a scaling measure that converts our proxy measure of consumer surplus to true consumer surplus for state i, and $\lambda_i \in [0,1]$ is state i's political preference for consumers or producers.

With reliable estimates of v_i and λ_i, we would expect for any two scenarios, k and k', if $W_{i,k} > W_{i,k'}$ then state i would rationalize a political decision to support outcomes that would bring about the k-scenario and undermine efforts that could manifest a k'-scenario. If $\lambda_{NC} = 1$, for instance, then the welfare measure of North Carolina would only consider consumer surplus. North Carolinians would support any inclinations by New Jersey, Maryland, or Virginia to defect from PJM's energy market and would raise issue with that same defection choice originating from Pennsylvania or Illinois.

[9] Technically, our simulations also show that Illinois is unambiguously better off under a Pennsylvania defection, but the changes in producers surplus and consumer wholesale costs are 0.06% and −0.03%, respectively.

We could also imagine a state including some climate goals in their welfare function such as setting a ceiling on allowable state-created CO_2 emissions. This would bring into consideration the emissions results from Table 9. Average cost to serve load after a state defection. A revised state welfare function might include a carbon constraint

$$W_{i,k} = (1 - \lambda_i)PS_{i,k} + \lambda_i v_i CS_{i,k} \qquad s.t.\ EM_{i,k} \leq \gamma_i \tag{5}$$

Where like terms carry the same definitions as in Equation 4, $EM_{i,k}$ is the annual CO_2 emissions of state i under simulation scenario k, and γ_i is a state-set maximum quantity of emissions.

DISCUSSION

Our analysis suggests a general tradeoff between producer and consumer welfare in other states if an individual state were to exit the PJM wholesale electricity market. How this would be valued by the remaining states would depend on the state's relative weighting of producer and consumer welfare (i.e., the from Equations [4] and [5]). These spillover effects may diminish the value of other states staying in the market, giving them pause to consider their own choice on defection. We see from Tables 11 and 12 that a New Jersey defection reduces producer surplus and increases consumer surplus in Maryland. Depending on Maryland's preferences toward producers and consumers, New Jersey's defection might decrease Maryland's overall welfare. If the decrease were large enough and if Maryland finds defection attractive enough, it might trigger Maryland's own exit. With both New Jersey and Maryland out, and if Virginia comes to a similar conclusion after its own calculations, then we might see a Virginia defection follow.

A full modeling of the counterfactual scenario to understand the welfare implications to the defecting state would allow future iterations of this research to include state defection as an endogenous choice. As hinted previously, we could foresee an investigation into the fragility of these organized markets. There may be certain conditions that compel one state to leave, creating a cascade of follow-on state defections as the whole consortium unwinds. Understanding the landscape that could bring about such a "collapse" would be valuable to state and federal regulators alike.

We note that our research does not address defections from capacity markets[10] or a total defection of both energy and capacity markets, but simulating these wholesale energy scenarios can help us better understand the spillover effects of exit shocks. Finally, our analysis does not value benefits of shared investment in transmission, nor does it consider any effects on system's reliability or resiliency. Building a model that considers these factors would lead to more accurate state welfare calculations.

CONCLUSION

This paper investigates the welfare effects on states that remain in an RTO following a state defection from the wholesale energy market. While reports have investigated the effects of a state defection from the PJM capacity market, our efforts give a fuller picture of the complexity of RTO coalitions and the potential instability that can unwind the collective. We find, generally, that if a net-importing state defects from the wholesale energy market, the remaining states' producers are worse off and the remaining states' consumers are better off. The opposite effect takes hold if the defecting state is a net exporter. The overall welfare ramifications depend on how a state values producer surplus relative to consumer surplus.

[10] Capacity market defection scenarios have already been explored in two independent market monitor reports (Monitoring Analytics 2020a, 2020b).

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APPENDIX A: DATA

We chose to simulate PJM using 2019 data, which provided the right balance of accurate generator data and timely policy inferences. Our research was complicated by the unusual geographic relationship of PJM between states and transmission zones. As should be expected with a coalition that started as three utilities in 1927 and grew to become the largest RTO in the Western Hemisphere, the growth of the organization did not cut specifically along state lines. The expansion of PJM, rather, took step changes with the integration of existing transmission systems. The PJM transmission zones of today are shown in Figure 3. PJM transmission zones (PJM 2021a) of the main text.

Figure 3. PJM transmission zones (PJM 2021a) clearly shows many transmission zones spanning one or more states, requiring us to apply assumptions as we simulated the exit of different states from the RTO. But first, we needed to create a model of PJM that accurately captures the pricing variability over the course of 2019.

To initialize our model, we gathered detailed data on the demand for electricity in PJM, the set of generators deployed in PJM, fuel costs associated with these generators, renewables generation in PJM's footprint, energy storage assets, transmission constraints present between PJM zones, imports/exports between PJM and external grid systems, and imports/exports between states within PJM.

A.1 Demand for Electricity in PJM

We pull hourly metered load data from PJM Data Miner 2 for the 2019 calendar year. The data provides hourly load across 29 different "load areas." These load areas needed to be coerced into nine zone areas for which we had transmission constraint data (see Section A.6, Transmission Constraints Between Zones). The crosswalk between load areas and zone areas was done by hand. Demand was aggregated to these nine zone areas based on the corresponding load area assignment shown in Table A1.

Table A1. Load area and the corresponding zone area

Load Area	Name	Zone Area	Renewable Area
AECO	Atlantic Electric	EMAC	MIDATL
AEPAPT	American Electric Power	West	WEST
AEPIMP	American Electric Power	West	WEST
AEPKPT	American Electric Power	West	WEST
AEPOPT	American Electric Power	West	WEST
AP	Allegheny Power Systems	APS	MIDATL
BC	Baltimore Gas & Electric	SMAC	MIDATL
CE	Commonwealth Edison	COMD	WEST
DAY	Dayton Power & Light	West	WEST
DEOK	Duke Energy Ohio and Kentucky	West	WEST
DOM	Dominion	Dominion	SOUTH
DPLCO	Delmarva Power & Light	EMAC	MIDATL
DUQ	Duquesne Light Co	West	WEST
EASTON	Delmarva Power & Light	EMAC	MIDATL

Load Area	Name	Zone Area	Renewable Area
EKPC	East Kentucky Power Cooperative	West	SOUTH
JC	Jersey Central	EMAC	MIDATL
ME	MetEd	WMAC	MIDATL
OE	American Transmission Systems	ATSI	WEST
OVEC	Ohio Valley Electric Corporation	West	WEST
PAPWR	American Transmission Systems	ATSI	WEST
PE	PECO Energy	EMAC	MIDATL
PEPCO	Potomac Electric Power Company	SMAC	MIDATL
PLCO	PPL Electric Utilities	WMAC	MIDATL
PN	PennElec	PENE	MIDATL
PS	Public Service Electric and Gas	EMAC	MIDATL
RECO	Rockland Electric	EMAC	MIDATL
SMECO	Potomac Electric Power Company	SMAC	MIDATL
UGI	PPL Electric Utilities	WMAC	MIDATL
VMEU	Atlantic Electric	EMAC	MIDATL

Sources: PJM (2021a) and PJM (2021b)

Because our counterfactuals include considering the defection of a single state from the PJM consortium, we needed to understand hourly demand at the state level, noting that states sometimes contain multiple zone areas and that some zone areas span multiple states (see Figure 3. PJM transmission zones (PJM 2021a)). We assign by hand each of the 29 different load areas with readily available demand data to the county-state pairs that those load areas serve. Then, we assign weighted percentages of a particular load area to a particular state based on 2019 Census estimates of county populations. If, for instance, a PJM load area served two counties, one county in State A and one county in State B, we would split the hourly demand in that load area according to the population of each of the two counties. We document these population splits in Table A4. Nameplate capacity of generator-fuel types in PJM.

Table A2. Population percentages across PJM load areas

Load Area	Zone Name	Zone Area	State	Percent Split by Population
AECO	Atlantic Electric	EMAC	NJ	100%
AEPAPT	American Electric Power	West	TN	10.63%
AEPAPT	American Electric Power	West	VA	48.33%
AEPAPT	American Electric Power	West	WV	41.03%
AEPIMP	American Electric Power	West	IN	78.33%
AEPIMP	American Electric Power	West	MI	21.67%
AEPKPT	American Electric Power	West	KY	100%
AEPOPT	American Electric Power	West	OH	100%

Load Area	Zone Name	Zone Area	State	Percent Split by Population
AP	Allegheny Power Systems	APS	MD	16.01%
AP	Allegheny Power Systems	APS	PA	43.45%
AP	Allegheny Power Systems	APS	VA	9.70%
AP	Allegheny Power Systems	APS	WV	30.84%
BC	Baltimore Gas & Electric	SMAC	MD	100%
CE	Commonwealth Edison	COMD	IL	100%
DAY	Dayton Power & Light	West	OH	100%
DEOK	Duke Energy Ohio and Kentucky	West	KY	22.19%
DEOK	Duke Energy Ohio and Kentucky	West	OH	77.81%
DOM	Dominion	Dominion	NC	3.48%
DOM	Dominion	Dominion	VA	96.52%
DPLCO	Delmarva Power & Light	EMAC	DE	65.77%
DPLCO	Delmarva Power & Light	EMAC	MD	31.20%
DPLCO	Delmarva Power & Light	EMAC	VA	3.03%
DUQ	Duquesne Light Co	West	PA	100%
EASTON	Delmarva Power & Light	EMAC	MD	100%
EKPC	East Kentucky Power Cooperative	WMAC	KY	100%
JC	Jersey Central	EMAC	NJ	100%
ME	MetEd	WMAC	PA	100%
OE	American Transmission Systems	ATSI	OH	100%
OVEC	Ohio Valley Electric Corporation	West	OH	100%
PAPWR	American Transmission Systems	ATSI	PA	100%
PE	PECO Energy	EMAC	PA	100%
PEPCO	Potomac Electric Power Company	SMAC	DC	33.41%
PEPCO	Potomac Electric Power Company	SMAC	MD	66.59%
PLCO	PPL Electric Utilities	WMAC	PA	100%
PN	PennElec	PENE	PA	100%
PS	Public Service Electric and Gas	EMAC	NJ	100%
RECO	Rockland Electric	EMAC	NJ	100%
SMECO	Potomac Electric Power Company	SMAC	MD	100%
UGI	PPL Electric Utilities	WMAC	PA	100%
VMEU	Atlantic Electric	EMAC	NJ	100%

Sources: US Census (2019) and PJM (2021a)

A.2 Generators in PJM

A.2.1 eGRID 2019 Data

We employ the US Environmental Protection Agency's (EPA's) Emissions & Generation Resource Integrated Database (eGRID) from 2019, merging data at the unit, generator and plant level (EPA 2019). We keep generators with the balancing authority code of "PJM" and drop all others. Generators are filtered further to keep only those reported as "operating—in service" at the end of 2018. Our model does not account for any generator entries or exits in 2019 and so the total fleet of PJM generators comes to 3,211 units with a nameplate capacity of 213.6 GW.

We aggregate generators by coded prime mover and fuel type to create 23 different generator fuel types as shown in Table A3. We break out the amount of nameplate capacity of each generator fuel type in Table A4.

Table A3. Generator-fuel types and their descriptions

Type	Description
Battery Storage	Storage using battery technology
Coal CT	Combustion turbine burning coal
Coal steam	Bottoming plant burning coal
Gas CC	Combined cycle plant burning non-natural gas
Gas CT	Combustion turbine burning non-natural gas
Gas IC	Internal combustion engine burning non-natural gas
Gas steam	Bottoming cycle plant burning non-natural gas
Hydro	Hydropower
NG CC	Combined cycle plant burning natural gas
NG CT	Combustion turbine burning natural gas
NG FC	Fuel cell burning natural gas
NG IC	Internal combustion engine burning natural gas
NG steam	Bottoming cycle plant burning natural gas
Nuclear	Nuclear power
Oil CC	Combined cycle plant burning petroleum products
Oil CT	Combustion turning burning petroleum products
Oil IC	Internal combustion engine burning petroleum products
Oil steam	Bottoming cycle plant burning petroleum products
Pumped storage	Storage using the potential energy of dammed water

Type	Description
Solar	Solar photovoltaic
Solid steam	Bottoming cycle plant burning solid fuel (non-coal)
Wind	Wind turbine
Other	No information to categorize

Sources: EPA (2019)

Table A4. Nameplate capacity of generator-fuel types in PJM

Type	Nameplate Capacity	
	MW	Percent of Total
Battery storage	321.9	0.15%
Coal CT	24.0	0.01%
Coal steam	53,470.8	25.03%
Gas CC	118.5	0.06%
Gas CT	147.7	0.07%
Gas IC	449.4	0.21%
Gas steam	485.9	0.23%
Hydro	3,281.1	1.54%
NG CC	54,908.4	25.70%
NG CT	30,021.4	14.05%
NG FC	37.5	0.02%
NG IC	385.5	0.18%
NG steam	9,670.8	4.53%
Nuclear	34,466.6	16.13%
Oil CC	180.0	0.08%
Oil CT	3,545.6	1.66%
Oil IC	422.0	0.20%
Oil steam	2,822.8	1.32%
Pumped storage	5,103.3	2.39%
Solar	3,315.9	1.55%
Solid steam	1,220.9	0.57%
Wind	9,215.5	4.31%
Other	17.2	0.01%

Sources: EPA (2019)

The data show PJM capacity in 2019 is predominantly natural gas–fired combine cycle plants, coal-fired steam plants, nuclear plants, and natural gas–fired combustion turbine plants. These assets account for 80.92% of the 213.6 GW of nameplate capacity in PJM. Renewable assets—those of solar photovoltaics, wind turbines, and hydropower plants—represent only 7.4% of PJM capacity. The "Other" category comprises slightly less than 0.01%, and while we make some assumptions about the characteristics of this type of generator, we claim these assumptions have little effect on the outcomes of our simulations.

In addition to capacity, our eGRID 2019 data also offer details on generator location (both the assigned state and the geographic coordinates) and, for conventional assets, generator heat rate and generator emissions per fuel input for SO_2 (lb/MMBtu), NO_x (lb/MMBtu), and CO_2 (ton/MMBtu). We do not have data on part load heat rates or part load emissions intensities and instead assume that part load performance is identical to full load across these dimensions.

While there are 3,211 generators in PJM, the EMST treats renewables (solar, wind, and hydro) as must-take assets and models storage assets separately, leaving 2,069 conventional generators. To aid with determining hourly merit order, the EMST incorporates many characteristics of generation including ramp rate, spinning reserve (up and down), nonspinning reserve, startup heat input, startup costs, minimum uptime and downtime, no load heat input, and fast start capability. A full description of these assumptions applied to conventional generating assets can be found in the online supplemental information.

A.2.2 Form EIA-860 2019 Data

We merge our eGRID dataset with 2019 data from Form EIA-860. Data are connected through the Office of Regulatory Information Systems (ORIS) Plant Code, which is managed by the Department of Energy.

Form EIA-860 contained information on minimum load of these generators, allowing the EMST to represent the capabilities of the PJM fleet more accurately over the course of the year.

A.2.3 Matching Generators to Transmission Zone Areas

Generators were matched to one of nine zone areas using information such as state, county, and transmission/distribution system owner, data all available in the "2. Plant" file of Form EIA-860. When there was still ambiguity over zone area, the latitude and longitude of the generator was used in conjunction with the map of Figure 3. PJM transmission zones (PJM 2021a) to make assignments. The final placement of each generator is included in the online supplemental information.

A.3 Fuel Costs for Nonrenewable Generators

Natural gas prices to the electricity industry in 2019 are published by EIA with monthly and state resolution (EIA 2021). Coal prices for 2019 are similarly provided by EIA and were set to the price of coal shipments to the electric power sector by month and by state (EIA 2020). Some states were missing data on natural gas or coal prices for either a month or the whole year. To populate this missing information, we calculated monthly average prices of natural gas and coal (weighted by quantity purchased) using Form EIA-923, page 5 (Fuel Receipts and Costs). Data were sparse here: the Form EIA-923 2019 data contain 28 plants in PJM that reported natural gas expenditures and 15 plants in PJM that reported coal expenditures.

Oil prices were exclusively formed using weighted averages from 2019 Form EIA-923 data for PJM units, of which there were only 23 plants. We note there were 359 oil generators in PJM in 2019 and while our sample is small, we claim that the geographically relevant and monthly resolution of our formed oil prices are preferable to a nationwide oil price without monthly variability.

Finally, as with Daraeepour et al. (2019), we use $2,770/kg (or $0.85/MMBtu) for the price of uranium.

A.4 Renewable Assets in PJM

To calculate hydro generation in PJM, we pull hourly generation by fuel type from PJM Data Miner 2 for the 2019 calendar year and then isolate "hydro" from the fuel type data provided. We have no further information to subset hydro generation across any geographic scales, but we do need hydro generation in each of our nine zone areas. To calculate an hourly hydro generation value for each transmission zone, we aggregate the total capacity of hydro assets assigned to each zone and then assume that the fraction of total capacity in a particular zone represents the fraction of total hydro generation that occurred systemwide in any given hour.

PJM Data Miner 2 provides 2019 hourly wind generation and hourly solar generation broken up by three areas: "MIDATL," "SOUTH," and "WEST." We employ the crosswalk assignment of Table A1 and apply the aggregation method—described previously for hydro generation—to the wind fleet and the solar fleet in PJM, giving us hourly wind and solar production in each of our nine transmission zones.

A.5 Storage Assets in PJM

Storage asset data from eGRID 2019 is combined with 2019 Form EIA-860 Schedule 3.4 (Storage Data), matching by ORIS Plant Code. These data contain important simulation inputs like nameplate energy capacity (MWh), maximum charge rate (MW) and maximum discharge rate (MW). Additional assumptions applied storage assets in PJM to can be found in the online supplemental information.

A.6 Transmission Constraints Between Zones

A detailed design of PJM's transmission system is not publicly available. We model an aggregated transmission system that represents only regional transmission limits. This aggregating is provided by the Environmental Protection Agency (EPA) as part of the documentation for the National Electric Energy Data System (NEEDS) (EPA 2013). Using NEEDS, our model divides PJM into nine regions as depicted in Figure 2.

Table A5. Total transmission capacity (MW) between NEEDS regions in PJM

	EMAC	SMAC	WMAC	Dominion	West Nameplate Capacity	APS	PENE	ATSi	COMD
EMAC	-	1,095	6,900	0	0	0	0	0	0
SMAC	1,095	-	2,000	2,812	30	2,200	0	0	0
WMAC	6,900	2,000	-	0	0	0	3,565	0	0
Dominion	0	2,812	0	-	3,800	8,000	0	0	0
West	0	0	0	3,800	-	6,300	0	9,700	4,000
APS	0	2,200	0	8,000	6,300	-	3,200	2,731	0
PENE	0	0	3,565	0	0	3,200	-	0	0
ATSi	0	0	0	0	9.700	2,731	0	-	0
COMD	0	0	0	0	4,000	0	0	0	-

Sources: EPA (2013)

Table A5 presents the transmission capacity limits between NEEDS regions in PJM. These data were created in 2013 and our model, simulating 2019, needs to account for potential changes in transmission capacity between our model's zones. We modify the transmission capacity limits with the goal of reducing the gap between PJM's observed day-ahead market prices and the simulated prices generated by EMST. These changes to the NEEDS-provided transmission limits are shown in Table A6. Our changes to these transmission limits are supported by data reported by PJM through the Data Miner 2 repository (PJM 2021b). The largest change reflected in Table A6, for instance, is the total transmission capacity between the COMD and West regions. NEEDS reported a transmission limit of 4,000 MW (as seen in Table A5), yet PJM Data Miner 2 shows outflow of electricity from COMD to the rest of PJM has been as high as 8,500 MW in 2019. Since the only point of interconnection between COMD and the rest of PJM is through the West region, we increased the transmission limit between those two zones by the 4,000 MW indicated. Making these adjustments of transmission capacity between zones not only more realistically aligned with the true observed inter-region transmission but also served to bring our simulated prices in closer step with the reported prices from PJM.

Table A6. Increase in total transmission capacity limits between NEEDS regions in PJM relative to limits provided by EPA (2013)

	EMAC	SMAC	WMAC	Dominion	West Nameplate Capacity	APS	PENE	ATSi	COMD
EMAC	-	400	1,100	0	0	0	0	0	0
SMAC	400	-	1,000	900	0	800	0	0	0
WMAC	1,100	1,000	-	0	0	0	900	0	0
Dominion	0	900	0	-	0	0	0	0	0
West	0	0	0	0	-	0	0	0	4,500
APS	0	800	0	0	0	-	0	0	0
PENE	0	0	900	0	0	0	-	0	0
ATSi	0	0	0	0	0	0	0	-	0
COMD	0	0	0	0	4,500	0	0	0	-

Sources: EPA (2013)

A.7 Imports and Exports out of PJM

PJM Data Miner 2 Actual/Schedule Summary Report provides hourly flows actual flows across tie-lines that connect PJM to external grid systems. Using hand matching, we apply a crosswalk of the 22 tie-lines to the zone area-state pairs as shown Table A7. This allows the EMST to consider total energy flows out of the nine transmission areas the model simulates.

Table A7. Tie-line and the corresponding zone area-state pair

Tie-Line	Balancing Authority Name	Zone Area	State
ALTE	Alliant Energy Corporate Services, Inc - CA	COMD	IL
ALTW	Alliant Energy Corporate Services, Inc - CA	COMD	IL
AMIL	Ameren Transmission. Legal Name Ameren Services Company	COMD	IL
CIN	Cinergy Corporation	West	OH

Tie-Line	Balancing Authority Name	Zone Area	State
CPLE	Carolina Power & Light Company	Dominion	NC
CPLW	Carolina Power & Light Company	West	VA
CWLP	City Water Light & Power	COMD	IL
DUK	Duke Energy Carolinas, LLC (Transmission)	West	VA
HUDS	Hudson Transmission Project	EMAC	NJ
IPL	Indianapolis Power & Light Company	West	OH
LAGN	Louisiana Generation, LLC	WMAC	KY
LGEE	E.ON U.S. Services Inc (Louisville Gas & Electric)	WMAC	KY
LIND	Linden Variable Frequency Transformer	EMAC	NJ
MDU	Montana-Dakota Utilities Co.	COMD	IL
MEC	MidAmerican Energy Company	COMD	IL
MECS	Michigan Electric Coordinated System	ATSi	OH
NEPT	Neptune Regional Transmission System	EMAC	NJ
NIPS	Northern Indiana Public Service Company	COMD	IL
NYIS	New York Independent System Operator	PENE	PA
SIGE	Vectren - Southern Indiana Gas & Electric Co.	WMAC	KY
TVA	Tennessee Valley Authority ESO	West	VA
WEC	Wisconsin Energy Corporation	COMD	IL

Sources: PJM (2021a) and PJM (2021b)

APPENDIX B: EMST PRICE PERFORMANCE

Since demand inputs into the EMST are the observed demands in PJM in 2019, evaluating the performance of our simulation hinges on a comparison of prices. The higher the correlation of simulated prices and actual prices, the more confident we can be in the results of our model during counterfactual scenarios.

To begin, we plot a time series of actual day-ahead, RTO-wide hourly prices as reported through PJM Data Miner 2 and our RTO-wide hourly price generated by the EMST. These curves are shown in Figure B1. Observed and EMST-simulated PJM-wide prices in 2019. We also show only the first 1,000 hours of 2019 in Figure B2. Observed versus EMST prices in the first 1,000 hours of 2019.

Figure B1. Observed and EMST-simulated PJM-wide prices in 2019

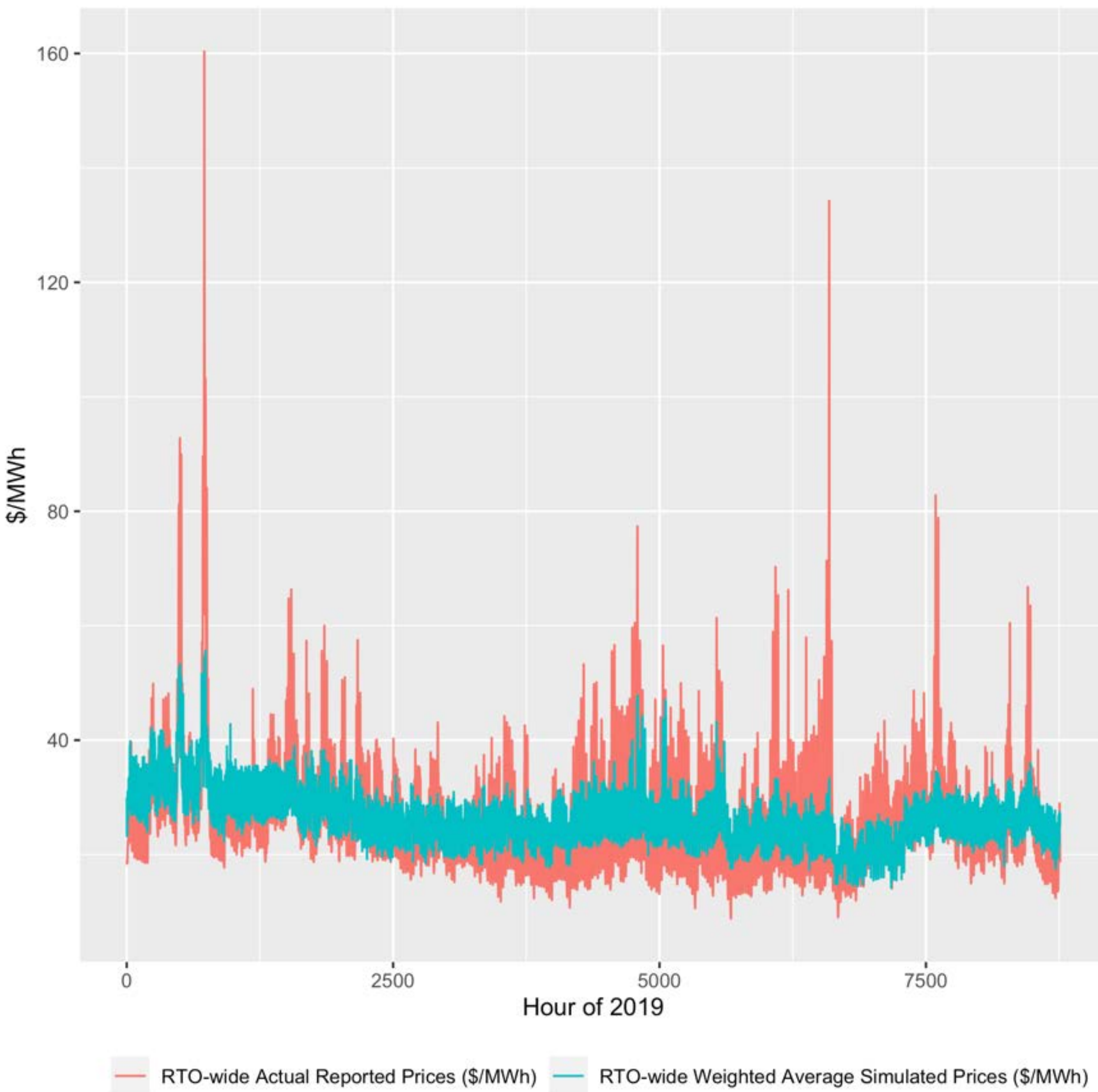
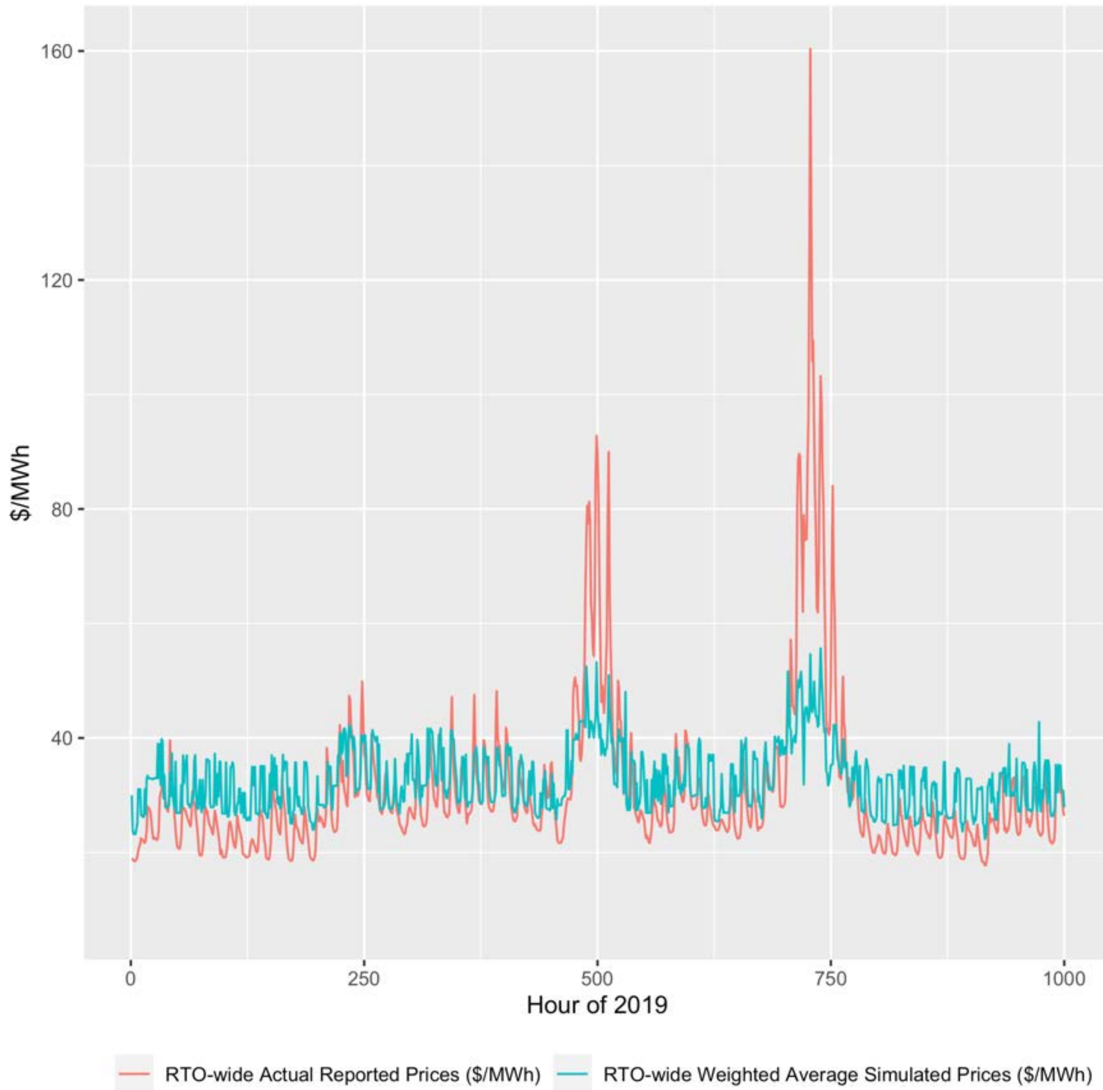


Figure B2. Observed versus EMST prices in the first 1,000 hours of 2019



It should be immediately apparent that while our simulation seems to perform well in many periods of 2019 (for instance, in the first approximately 480 hours of the year), the simulation does not capture enormous price spikes. The highest price spike of the entire year occurred in hour 728, corresponding to 7 a.m. Eastern Standard Time (EST) on Thursday January 31, 2019. This price spike and the high prices surrounding it were the result of an anomalous weather event that started to roll through Illinois on Tuesday morning and did not moderate until Friday, February 2, 2019. Temperatures were below 10°F RTO-wide and the actual morning low (not wind chill) temperatures on that Thursday morning dropped to –24°F in the Commonwealth Edison transmission area (PJM Operating Committee 2019a).[11] Of the top 33 hours of highest prices PJM faced in the 2019 calendar year, 20 of them occurred during the period spanning Wednesday January 30 and Thursday January 31. Within the 48-hour period described here, 32 of those hours were part of the top 100 prices of 2019. PJM explains these price spikes as being caused by a significant increase in load as the cold air mass moved through the system and forced outages reached as high as 10.6% of total PJM capacity (PJM Operating Committee 2019a).[12]

[11] Commonwealth Edison is represented as "COMD" in Figure 2. EMST transmission zones in PJM and "ComEd" in Figure 3. PJM transmission zones (PJM 2021a).

[12] The PJM Operating Committee (2019a) noted that the forced outages of the January 31, 2019, event of 10.6% of total PJM capacity was actually lower than the forced outage percentages of the 2014 polar vortex (22%) and 2018 winter peak (12.1%), pointing to the fact that prices could have been higher during this 2019 cold-weather event had outages been more in line with historical performance.

The second highest price spike as depicted in Figure B1 occurred between October 1 and October 2, 2019. Here, an unforeseen heat wave increased demand and forced PJM to engage in emergency procedures, including the first time demand response resources were tapped in over five years (PJM Operating Committee 2019b). The impact was less persistent compared to the January cold snap, but eight hours during this heat wave were part of the 100 highest prices in PJM.

EMST did capture an artifact of these events through the demand that the system experiences. We see in Figure B2. Observed versus EMST prices in the first 1,000 hours of 2019 that prices predicted by EMST do spike under the load spike that accompanied the winter event of late January. Yet, while EMST does capture the demand-side components of any exogeneous event, the model does not simulate unplanned outages (caused by weather or some other factor) and so cannot predict supply side shocks.

We drop the 48 hours surrounding the January winter event and the 48 hours surrounding the October heat wave and then calculate the descriptive statistics comparing actual prices to simulated prices. These results are shown in Table B1.

Table B1. Descriptive statistics of 2019 prices without the January and October weather events

Time Series	Obs	Mean, \$/MWh	Std. Deviation, \$/MWh	Median, \$/MWh	Min., \$/MWh	Max., \$/MWh	Skew	Kurtosis
Observed	8,664	25.68	8.14	24.31	8.8	92.79	1.71	6.37
EMST	8,664	26.34	4.77	26.03	14.23	53.24	0.79	1.36

After dropping these 96 hours of exogeneous events, we see that EMST continues to be a good predictor of price levels but does a better job of representing actual price variation, skew and kurtosis (see Table 1 in the main text for a comparison).

A correlation analysis after dropping these weather shocks was also employed, using the Pearson's product-moment correlation, Spearman's rank correlation coefficient, and Kendall's rank correlation coefficient. Table B2 shows a decrease in correlation when we omit the weather event hours. This is likely because EMST successfully captures the demand side shock: the simulation predicts increasing prices, which matches trends in real prices.[13] Dropping these hours, then, omits observations with high correlation and reduces the reported values seen in Table B2.

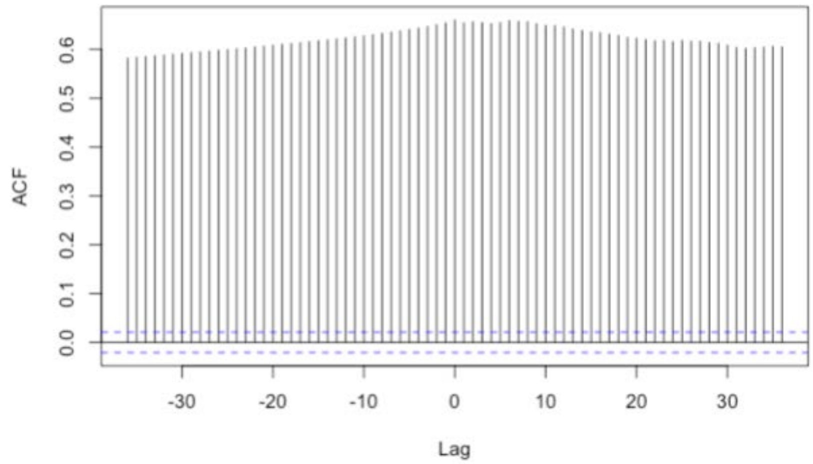
Table B2. Correlation between actual and simulated prices with and without weather events

Time Series	Obs.	Pearson's Product-Moment Correlation	Spearman's ρ	Kendall's τ
Full year	8,760	0.6595771	0.6668497	0.482096
Drop weather-related 96 hours	8,664	0.649502	0.6613582	0.476906

We also confirm no cross-correlation with lagged factors between EMST-generated prices and real prices. Figure B3 shows the highest correlation between actual and simulated prices when there is zero lag.

[13] The highest actual price in PJM occurs at 7 a.m. EST on January 31, 2019. During that same hour, EMST predicts the second-highest price of the year. The scale, though, is dramatically different. Actual prices were reported as \$160.35/MWh during this hour, while EMST calculated prices would clear at \$54.63/MWh. Some of this difference could most certainly be explained by the supply-side shock experienced by PJM that our simulation does not capture.

Figure B3. Autocorrelation function analysis for actual and simulated prices



We argue there are two primary factors that create discrepancies between EMST-created prices and actual prices. First, as discussed previously, EMST does not account for supply-side shocks that can contribute to higher observed price spikes. Second, EMST considers nine transmission zones because of limitations on available transmission data, wheras PJM sets locational marginal pricing across more than 5,700 nodes (PJM 2021b). Congestion-related events are dampened by the coarser grid that EMST models, providing another pathway through which prices are artificially suppressed compared to observed values.

Despite the shortcomings of EMST in predicting actual prices, it seems these issues are only prevalent when some shock is impacting the grid, be it a weather event or other issue that leads to unplanned grid congestion and/or forced outages. That the model does not capture these effects speaks to the quality of the simulation: EMST is not creating artifacts in its data-generating process and any divergence between simulated prices and observed prices is likely the result of an exogeneous shock.

We conclude that EMST provides a reliable avenue through which to predict profits to generating assets, the average cost to serve load, and the emissions intensity of the dispatched system for both the PJM base case and instances where a state defects from the consortium.

JEL Codes

Q41, Q48

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