Appendix

EVALUATING THE ECONOMIC BENEFITS OF PENNSYLVANIA'S DECISION TO JOIN THE REGIONAL GREENHOUSE GAS INITIATIVE

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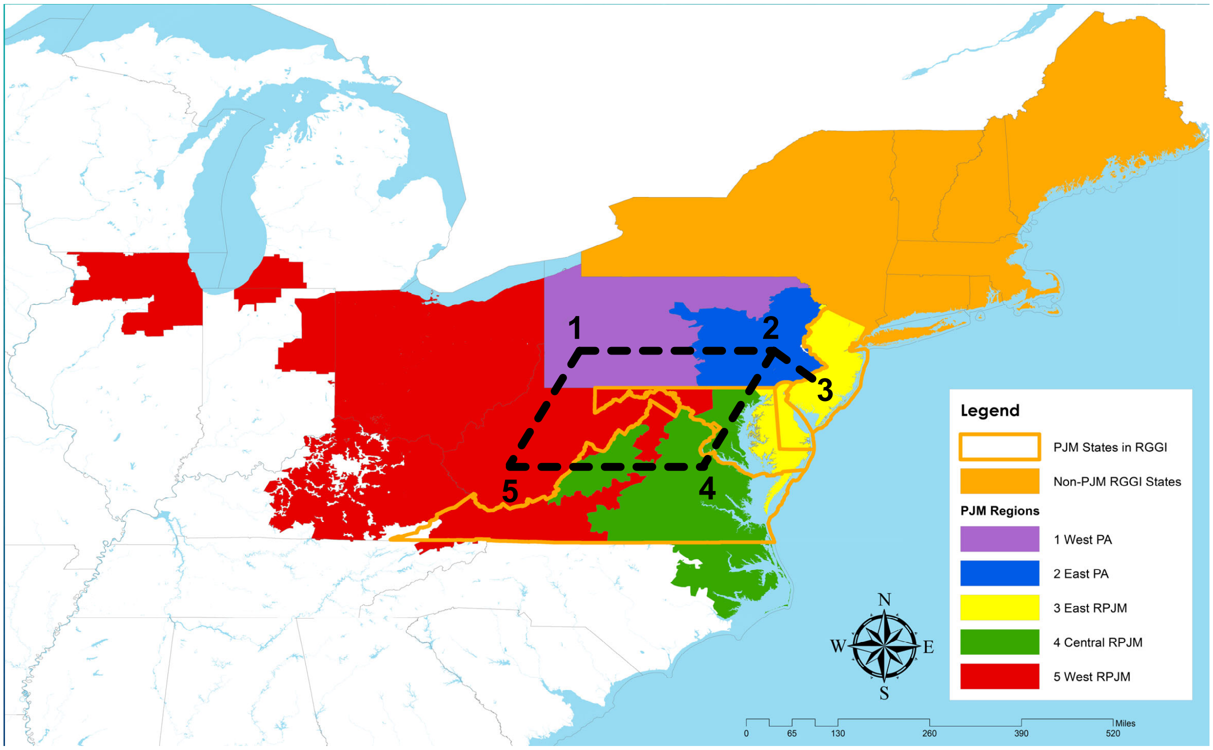
Section 1 provides a detailed overview of the simulation model. Section 2 presents the functional forms used in the simulation model. Section 3 discusses the parameter values and data sources used for calibration. Section 4 outlines the assumptions and data sources used to generate emissions estimates. In Section 5 we outline the assumptions regarding the dynamic trends that underlie our simulation results. Pre-existing polices that we account for in our analysis are described in Section 6. Section 7 reports our model calibration results. Section 8 validates our baseline against historical data. Finally, Section 9 presents additional results not reported in the main text.

1 Model Overview

The RGGI+PJM Policy Analysis Model (RPAM) is a multi-market numerical simulation model that combines: 1. a direct current optimal power flow (DCOPF) model of the PJM power system; 2. the endogenous supply of new generation capacity within PJM; 3. the importation of Renewable Energy Credits (RECs) from outside of PJM; 4. the supply of CO_2 abatement from non-PJM Regional Greenhouse Gas Initiative (RGGI) states; and 5. the supply/demand of banked CO_2 allowances from current RGGI market participants. Parts 1-3 of the model is calibrated using data for 2016 and 2017 collected from over a dozen sources and is validated using 2018 data across several dimensions: REC prices, locational marginal prices (LMPs), predicted new capacity, and generation mix. Parts 4 and 5 are jointly econometrically estimated using historical data on emissions, caps, permits sold at auction, and allowance price data from RGGI. RPAM operates on an annual time-step and we simulate outcomes from 2018 to 2030. The RPAM domain is depicted in Figure A.1.

Figure A.1: RGGI+PJM Policy Analysis Model (RPAM) Domain



As shown in Figure A.1, RPAM consists of five regions (purple, blue, yellow, green, and red) which comprise the wholesale electricity market operated by PJM as well as the CO_2 emissions released by RGGI states that are not in PJM (solid orange). In addition, a subset of states are members of RGGI and are also wholly or partly contained with PJM's system boundaries (orange outline) and allowances added to the RGGI allowance bank prior to 2022 are assumed to be held by market participants within all current RGGI states (solid orange or outline orange).

The black dashed lines depict the five aggregate transmission lines which link these five regions: A. line 12 connects West Pennsylvania and East Pennsylvania; B. line 23 connects East Pennsylvania and East RPJM; C. line 24 connects East Pennsylvania and Central RPJM; D. line 45; and, E. line 15 connects West Pennsylvania and West RPJM. These five lines are constructed based upon visual inspection of the transmission linkages between the five regions. There are no direct links between East Pennsylvania and West RPJM, West Pennsylvania and East RPJM, West Pennsylvania and Central RPJM, East RPJM to Central RPJM, or East RPJM to West RPJM. While these lines capture the aggregate physical location of transmission lines across PJM, the transmission constraints are numerically calibrated to replicate the generation-weighted average inter-regional difference in LMPs. RPAM also has 96 load segments, constructed from 8,784 hours in 2016 and 8,760 hours in 2017. Within each PJM region, we assume that demand for electricity is partially inelastic across 96 load segments. Details on how we construct the five aggregate regions, 96 load segments, demand elasticity and transmission lines are discussed in sections 3.1 and 2.5.

The supply side considers the economic decisions of 843 representative existing generation units (EGUs) which have been aggregated from a population of 3,095 EGUs located within PJM and whose locations are known. Fuel costs facing generators vary across region and are allowed to vary daily reflecting correlation with load. Given predicted generation from representative EGUs, generation and emissions can be descaled to the full population of EGUs across the landscape. RPAM also allows for endogenous new capacity expansion in natural gas combined cycle (NGCC), solar, and wind. Details on calibrations for the supply side can be found in section 3.2.

2 Functional Forms

2.1 Regional Demand for Electricity

The regional direct economic benefits from consuming electricity in region i at a representative hour in load segment l are given by:

$$DB_{il}\left(d_{il}\right) = c_{il}d_{il} - \frac{n_{il}}{2}\left(d_{il}\right)^2, \tag{1}$$

where d_{il} is the electricity demand in region i at a representative hour in load segment l, n_{il} and c_{il} are the slope and intercept of the linear inverse demand curve implied by the first-order conditions for the numerical model with respect to d_{il}: $p_{il} = c_{il} - n_{il}d_{il}$, where p_{il} is the price of electricity in region i at load segment l.

2.2 Supply of Electricity from Existing Generation

The direct economic costs from existing representative electric generating unit (EGU) j located in region i and supplying electricity in a representative hour in load segment l are given by:[1]

$$DC_{jl}^{E}\left(g_{jl}^{E}\right) = b_{jl}^{E}g_{jl}^{E} + \frac{m_{jl}^{E}}{2}\left(g_{jl}^{E}\right)^2, \tag{2}$$

where g_{jl}^{E} is the electricity generation supplied by existing EGU j in a representative hour in load segment l, m_{jl}^{E} and b_{jl}^{E} are the slope and intercept of the linear inverse supply curve for existing EGU j in region i at any given hour in load segment l implied by the first-order conditions for the numerical model with respect to g_{jl}^{E}: $p_{il} = b_{jl}^{E} - m_{jl}^{E}g_{jl}^{E}$.

In addition, each representative existing EGU j has a limit on the amount of power they can

[1] For some existing EGUs, costs here also account for the costs of complying with Title IV of the Clean Air Act and state nuclear subsidies. See Appendix Sections 3.2.2 and 6 for additional details.

supply in a representative hour in each load segment l reflecting their available effective capacity:

$$g_{jl}^{E} \leq K_{jl}^{E}, \tag{3}$$

where K_{jl}^{E} is EGU j's effective capacity in any given hour in load segment l [2].

2.3 New Capacity and Supply of Electricity from New Generation

The direct economic costs from operating a new EGU j in region i and supplying electricity in a representative hour in load segment l are given by:

$$DC_{jl}^{N}\left(g_{jl}^{N}\right) = b_{jl}^{N} g_{jl}^{N}, \tag{4}$$

where g_{jl}^{N} is the electricity generation supplied by new EGU j in a representative hour in load segment l, b_{jl}^{N} is the private marginal operating cost for new EGU j in a representative hour in load segment l.

Additionally, each new EGU j has a limit on the amount of electricity generation it can produce each hour in a load segment, reflecting its available effective capacity:

$$g_{jl}^{N} \leq K_{j}^{N}, \tag{5}$$

where K_{j}^{N} is the effective capacity of new EGU j at any given hour, which is calculated as follows: $K_{j}^{N} = \bar{K}_{j}^{N}\gamma_{j}^{N}$, where $\bar{K}_{j}^{N}$ is the total amount of new capacity that is expanded for new EGU j, measured in MW, and γ_{j}^{N} is the utilization factor from new EGU j, which is discussed in section 3.3.

The direct economic costs of adding one new MW of capacity for new EGU j in a given year

[2] Effective capacities of existing EGUs are discussed in details in Appendix Section 3.2.3.

are given by:

$$CC_j^N\left(\bar{K}_j^N\right) = C_j^N \bar{K}_j^N, \tag{6}$$

where C_j^N is the marginal costs of adding one MW of new capacity to new EGU j.

2.4 External Renewable Energy Certificates

We allow Renewable Energy Certificates (RECs) generated by EGUs outside of PJM to be used for compliance with various state Alternative Energy/Renewable Portfolio Standards (RPSs), which often have multiple tiers, within PJM, reflecting their historical importance for compliance with state RPSs. Let r_{qst} be the amount of tier t RECs that an EGU q outside of PJM supplies to state s in PJM. The total amount of external RECs that that EGU q can supply in a given year across all the states with RPSs within PJM must satisfy:

$$\sum_{st\in\mathcal{ST}_q} r_{qst} \leq r_q, \tag{7}$$

where r_q is the total amount of external RECs that external EGU q can supply to a subset of states with RPSs in PJM in a given year across all tiers, which is defined as $r_q = \bar{r}_q\gamma_q$, where $\bar{r}_q$ is the total amount of external RECs that external EGU q can supply to all states (including states that are outside of PJM) in a given year, and γ_q is the percentage of $\bar{r}_q$ that indicates the total amount of external RECs that external EGU q can supply only to states in PJM. Calibration of γ_q is discussed in details in section 3.4.

$\mathcal{ST}_q$ is the subset of states and tiers for which external EGU q can supply external RECs. The marginal revenue received by the external REC supplier reflects the REC prices that emerge endogenously from our model as discussed below, reflecting zero marginal costs. Effectively, (7) ensures that external RECs are distributed to states across PJM with the highest REC prices first until the supply of external RECs is exhausted. After the model is solved for, aggregate surplus by state is adjusted by the costs of external RECs purchased by the state in light of the equilibrium

REC prices that are realized, as discussed below.

2.5 Transmission Network

Net power flow into region i from another region h at any given representative hour in load segment l must not exceed the effective capacity constraint of the transmission line between the two regions at that load segment:

$$-\bar{f}_{ihl} \leq f_{ihl} \leq \bar{f}_{ihl} \tag{8}$$

where f_{ihl} is the net flow of electricity into region i from region h at load segment l and $\bar{f}_{ihl}$ is the maximum effective transmission capacity between region i and h at load segment l, all of which are measured in MWh. The sign indicates the direction of the power flow, with a negative sign denoting power is flowing away from i and a positive sign that power is flowing into i. $\bar{f}_{ihl}$ is calculated as follows: $\bar{f}_{ihl} = V_{ihl}A_{ihl}$, where V_{ihl} is the net voltage of the transmission line between region i and region h during load segment l in volts, and A_{ihl} is the electrical current between region i and region h during load segment l in amperes. Details on how we calibrate V_{ihl} and A_{ihl} are discussed in section 3.5.

2.6 CO_2 Emissions from RGGI States Outside of PJM

The direct economic benefit to covered EGUs in RGGI states that are not in PJM is given by:

$$DB^{NPJM}\left(E^{NPJM}\right) = c^{NPJM}E^{NPJM} - \frac{n^{NPJM}}{2}\left(E^{NPJM}\right)^2, \tag{9}$$

where E^{NPJM} is the CO_2 emissions from covered EGUs in RGGI states outside of PJM, n^{NPJM} and c^{NPJM} are the slope and intercept, respectively, of the linear inverse abatement curve for non-PJM RGGI states in a given year implied by the first-order condition with respect to E^{NPJM}: $p^{RGGI} = c^{NPJM} - n^{NPJM}E^{NPJM}$, where p^{RGGI} is the RGGI allowance price in that year.

2.7 Supply/Demand of Banked Allowances

The direct economic benefit to holders of allowances that have been banked historically from previous years is given by:

$$DB^{B}\left(B,\bar{B}\right)=c^{B}\left(\bar{B}\right)B-\frac{n^{B}}{2}\left(B\right)^{2}, \tag{10}$$

where B is the total amount of RGGI allowances in the RGGI allowance bank in a given year, n^B and $c^B\left(\bar{B}\right)$ are the slope and intercept, respectively of the linear inverse RGGI banked allowance curve, implied by the first-order condition for the numerical model with respect to B: $p^{RGGI}=c^B-n^B B$. As discussed further below in later Appendix Sections, n^B is fixed across years whereas $c^B\left(\bar{B}\right)$ is a function of the bank account balance as of the end of the previous year, $\bar{B}$. $\bar{B}$ reflects withdrawals ($B-\bar{B}<0$) or additions ($B-\bar{B}>0$) identified by the previous years' model solutions from an initial bank account balance in 2019 calculated from historical RGGI auction and cap data.

Across years the bank account balance evolves according to:

$$\bar{B}\equiv\bar{B}_{y-1}=B_{y-1}, \tag{11}$$

where $\bar{B}_{y-1}$ is the bank account balance at the end of the previous year and B_{y-1} is the amount of permits withdrawn or added to the bank in the previous year.

Additionally, the number of banked allowances available in a given year cannot be negative:

$$B\geq 0. \tag{12}$$

2.8 Market Clearing Conditions

2.8.1 Electricity Market

The electricity market clears in region i at a representative hour in load segment l when the following constraint is satisfied:

$$\sum_{j\in\mathcal{J}_i} g_{jl}^E + \sum_{j\in\mathcal{J}_i} g_{jl}^N + \sum_{h\in\mathcal{L}_i} f_{ihl} \geq d_{il}\left(1+\epsilon_l\right) \quad \text{for all } i, l, \tag{13}$$

where $\mathcal{J}_i$ is the set of all new and existing EGUs in PJM region i, $\mathcal{L}_i$ is the set of all nodes that are connected to i, and ϵ_l is aggregate loss in any given hour in load segment l as a percentage of demand in region i for that hour, which reflects transmission and distribution system losses as well as the difference in virtual increment offers and decrement bids, as discussed further below in section 3.6.

2.8.2 Renewable Energy Credit Markets

Several states s within PJM have multiple tiers t (e.g., tier 1, tier 2 and solar RPS) of Renewable/Alternative Energy Portfolio Standards (RPS) which mandate that at least a certain fraction of generation in a given year come from 'numerator EGUs' (RPS eligible EGUs) for a given state-tier st relative to total generation in that state. Similar to other mandate and trade systems (e.g., the Renewable Fuel Standard, Corporate Average Fuel Economy Standards), state-tier RPSs allow for the restricted trade of virtual renewable energy credits (RECs) among market participants that are eligible (and in some cases, required) to participate under each state-tier RPS st. The REC market clears for each RPS state-tier combination st in a given year according to:

$$\frac{\sum_{j\in\mathcal{J}_{st}}\sum_l \delta_l\left(g_{jl}^E + g_{jl}^N\right) + \sum_{q\in\mathcal{Q}_{st}} r_{qst}}{\sum_{j\in\mathcal{J}_s}\sum_l \delta_l\left(g_{jl}^E + g_{jl}^N\right)} \geq \bar{R}_{st}, \tag{14}$$

where δ_l is number of hours in load segment l, $\bar{R}_{st}$ is the RPS target of tier t in state s in a given year, $\mathcal{Q}_{st}$ is the subset of external EGUs which can supply external RECs for compliance with the st RPS standard, $\mathcal{J}_{st}$ is the subset of new and existing EGUs in PJM which are allowed to enter the numerator of state-tier RPS constraint st, and $\mathcal{J}_s$ is the subset of denominator new and existing EGUs for each state s (which is common across tiers for all states in PJM and includes all the existing and new EGUs in that state). See Appendix Section 6.4 for further details.

2.8.3 RGGI Allowance Market

So far all states that have decided to join RGGI have chosen to allow inter-state allowance trading among RGGI market participants. As a result there is a single market for RGGI allowances which clears in a given year according to:

$$\sum_{j \in \mathcal{J}_{RGGI}} \sum_{l} \delta_l \left(\phi_j^{E,\mathrm{CO}_2} g_{jl}^{E} + \phi_j^{N,\mathrm{CO}_2} g_{jl}^{N} \right) + E^{NPJM} + \left(B - \bar{B} \right) \leq \sum_{s \in \mathcal{S}_{RGGI}} \bar{E}_s^{RGGI} \tag{15}$$

where $\bar{E}_s^{RGGI}$ is the adjusted cap assigned to state s consistent with its membership in RGGI, $\mathcal{J}_{RGGI}$ is the subset of covered new and existing EGUs in PJM that are also in states that are members of RGGI, $\mathcal{S}_{RGGI}$ is the subset of states that are members of RGGI in a given year, ϕ_j^{E,CO_2} is the CO_2 emissions rate of existing EGU j, and ϕ_j^{N,CO_2} is the CO_2 emissions rate of new EGU j (here, assumed to include just natural gas combined cycle (NGCC)).

2.8.4 Characterization of the Competitive Equilibrium

There are multiple ways to numerically solve for the competitive equilibrium solution which effectively reflects: 1. the PJM system operator's optimal hourly dispatch decision assuming DCOPF; 2. the decentralized annual power system capacity investment equilibrium; 3. the decentralized REC equilibrium; and 4. the decentralized RGGI allowance market equilibrium, conditional on all other (exogenous) pre-existing policies. According to the First Fundamental Welfare Theorem and the assumptions of our model the most direct solution method involves solving 1 across all hours of the year, but allowing for new capacity investment and conditional on market clearing in the REC and RGGI allowance markets. In this case the objective function to maximize is:

$$\sum_i \sum_l \delta_l \left(c_{il} d_{il} - \frac{n_{il}}{2} \left(d_{il}\right)^2 \right) - \sum_j \left[C_j^N \bar{K}_j^N + \sum_l \delta_l \left(b_{jl}^E g_{jl}^E + \frac{m_{jl}^E}{2} \left(g_{jl}^E\right)^2 - b_{jl}^N g_{jl}^N \right) \right]$$
$$+ \left[c^{NPJM} E^{NPJM} - \frac{n^{NPJM}}{2} \left(E^{NPJM}\right)^2 \right] + \left[c^B B - \frac{n^B}{2} \left(B\right)^2 \right] \tag{16}$$

given (1), (2), (4), (6), (9), and (10). Thus, a *competitive equilibrium* is the quantities and (shadow) prices that are returned from maximizing (16), choosing $d_{il} \forall i, l$, $g_{jl}^E \forall j, l$, $g_{jl}^N \forall j, l$, $r_{qst} \forall q, s, t$, $\bar{K}_j^N \forall j$, E^{NPJM}, B and $f_{ihl} \forall i, h, l$ and subject to (3), (5), (7), (8), (12), (13), (14), (15), and non-negativity constraints on d_{il}, g_{jl}^E, g_{jl}^N, r_{qst}, $\bar{K}_j^N$, E^{NPJM}, and B.

3 Data and Calibration

In this section, we discuss the data and intermediate steps to calibrate the parameters listed in Table A.6. We calibrate our model primarily using 2016 and 2017 historical data. Since we use up-to-date EGUs data in 2016 from various data sources, our model does not include capacity expansion in 2016. In 2017, our model allows capacity expansion of new NGCC, wind and solar EGUs to be added to the set of EGUs that can be dispatched by PJM. Finally, the non-PJM RGGI marginal benefits from emissions and the marginal benefits of banked allowances are estimated using more recent data from the inception of RGGI in 2009 through 2019.

3.1 Demand

3.1.1 Load Regions

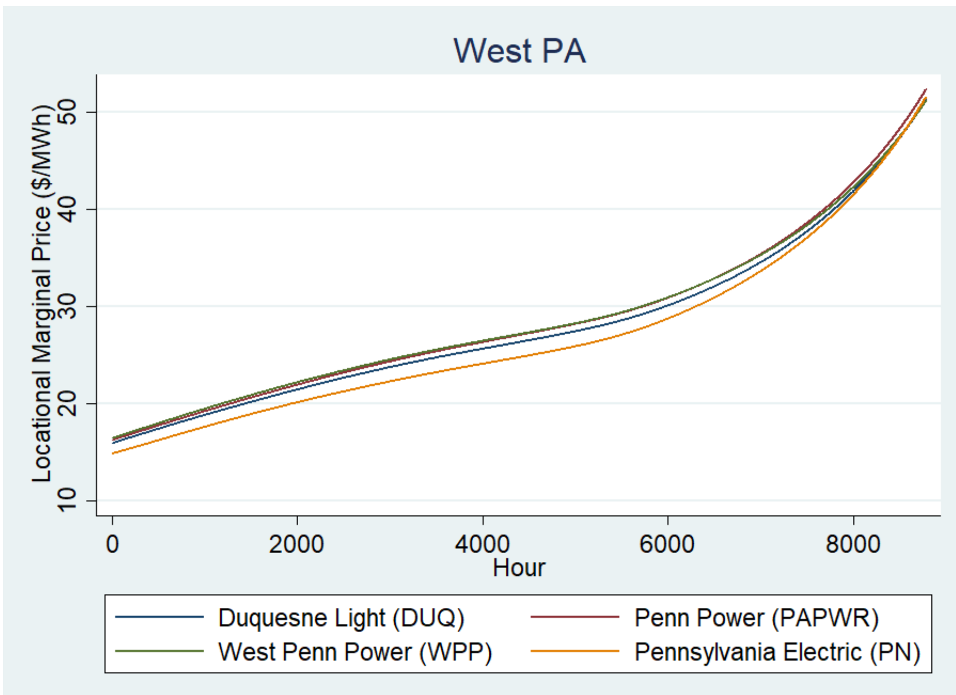
The five regions that comprise PJM in RPAM are constructed by aggregating load zones in PJM based on similarity across day-ahead hourly locational marginal prices (LMPs) taken from the *Day-Ahead Hourly LMPs for 2016* dataset from *PJM Data Miner 2: //dataminer2.pjm.com/feed/da_hrl_lmps/* (accessed 05/15/2017),[3] and geographical proximity in Pennsylvania and Rest of PJM (RPJM) (only zones that are adjacent to each other or adjacent to a zone in common can be aggregated). The five regions are: 1. West Pennsylvania (purple), which includes West Penn Power (the Pennsylvania part of Allegheny Power), Penn Power (the Pennsylvania part of American Transmission Systems Inc), Duquesne Light Company, and the Pennsylvania Electric Company; 2. East Pennsylvania (blue), which includes the Metropolitan Edison Company, PPL Electric Utilities Corporation, and the PECO Energy Company; 3. East RPJM (yellow), which includes Atlantic City Electric Company, Jersey Central Power and Light Company, Public Service Electric and Gas Company, Delmarva Power and Light Company and Rockland Electric Company; 4. Central RPJM (green), which includes Baltimore Gas and Electric, Dominion, and Potomac Electric; and, 5. West RPJM (red), which includes the non-Pennsylvania part of Allegheny

[3]The five figures below show day-ahead hourly LMPs for these load zones based upon the RPAM PJM regions they are grouped into, given a curve smoothing bandwidth of 0.8, and after sorting hours in the year from lowest to highest load.

Power, American Electric Power Company, the Ohio part of American Transmission Systems Inc, the Commonwealth Edison Company, Duke Energy Ohio and Kentucky, East Kentucky Power Cooperative Inc, and the Dayton Power and Light Company.

Figure A.2 shows the sorted day-ahead LMPs in 2016 for the four load zones that make up the West Pennsylvania region in RPAM. The LMP in West Pennsylvania in the lowest demand hour is as low as approximately $15/MWh and the LMP in the highest demand hour is more than $50/MWh. The median LMP is around $27/MWh.

Figure A.2: Day-ahead LMPs in West Pennsylvania in 2016



Similarly, Figure A.3 provides the sorted day-ahead LMPs of the three load zones that make up East Pennsylvania. The LMP in the lowest demand hour is close to $5 per MWh and LMP in the highest demand hour is over $50. The median LMP is approximately $22. Overall, West Pennsylvania observes higher LMPs than East Pennsylvania in 2016, although there is some convergence in LMPs during high demand periods.

Figure A.3: Day-ahead LMPs in East Pennsylvania in 2016

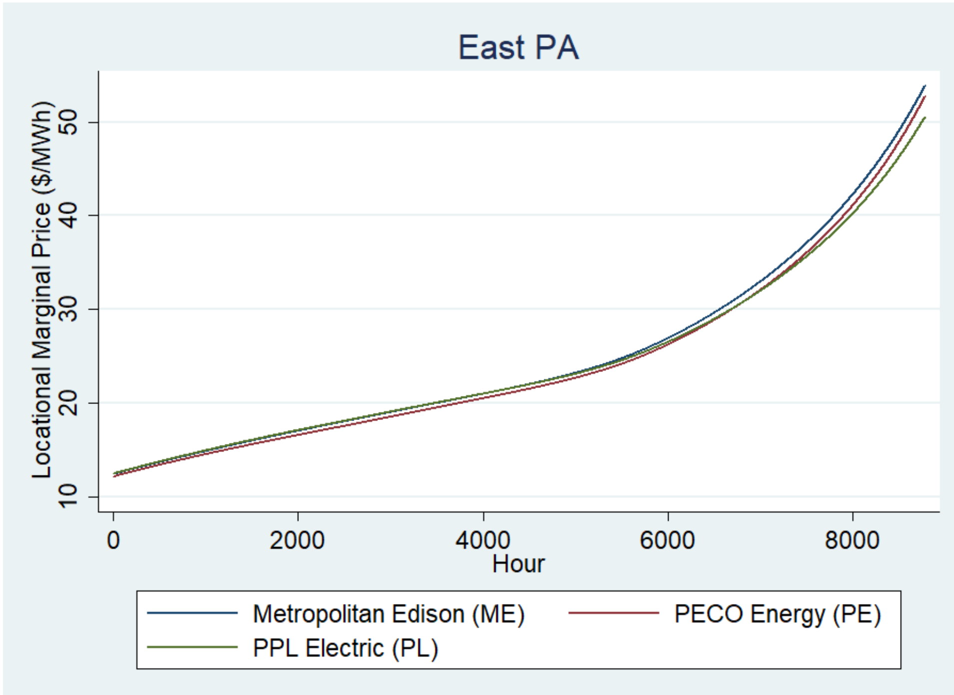
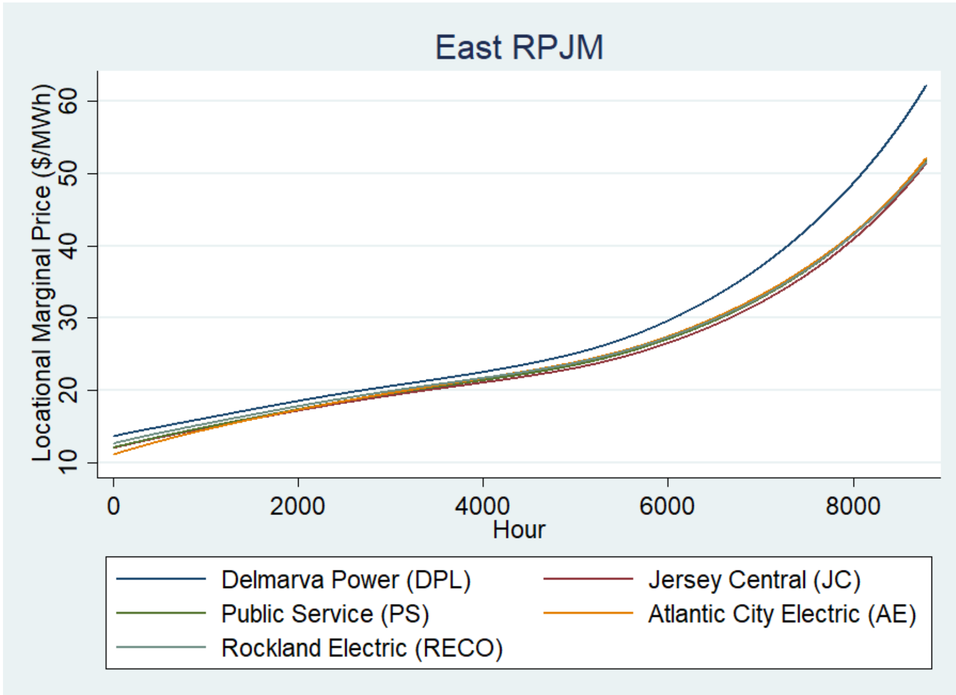


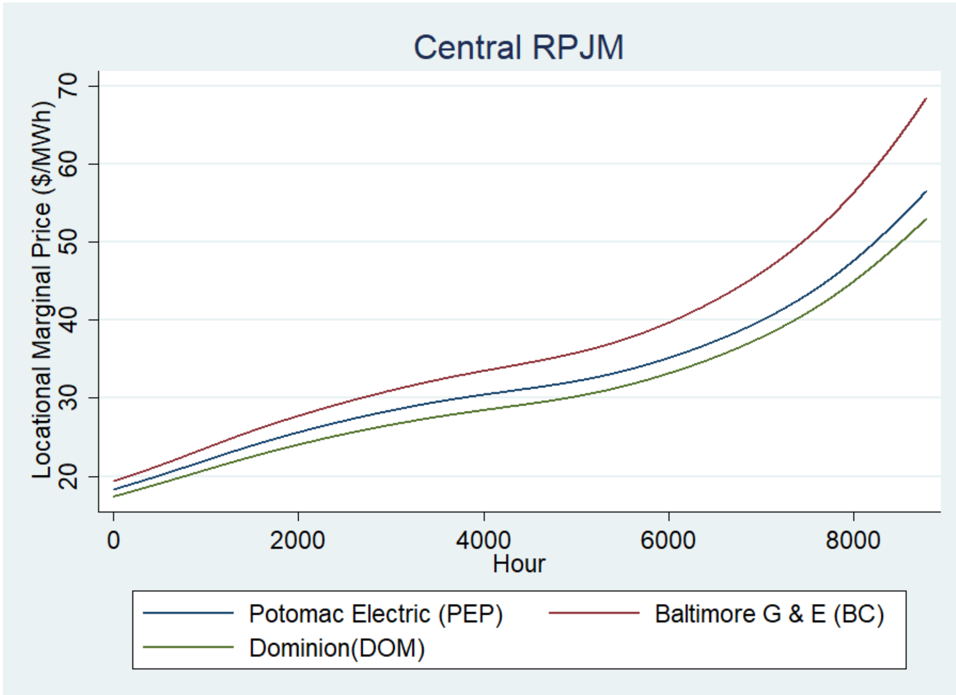
Figure A.4 present the sorted day-ahead LMPs of the five load zones which constitute East RPJM. LMPs in the lowest demand hour is as low as $11 per MWh and LMPs in the highest demand hour is more than $60 for the DPL zone and more than $50 for the other zones. The median LMP is around $22.

Figure A.4: Day-ahead LMPs in East RPJM in 2016



Similarly, Figure A.5 shows sorted day-ahead LMPs for the three load zones which comprise Central RPJM. LMPs in this region are the most spread out with a LMP in the low demand hour of approximately $18 per MWh and a LMP near $69 in the highest demand hour. The median LMP lies just above $30.

Figure A.5: Day-ahead LMPs in Central RPJM in 2016



Finally, Figure A.6 shows sorted day-ahead LMPs of the seven load zones which make up West RPJM. The LMP in the lowest demand hour is nearly $15 per MWh. The LMPs in the 2,000 highest demand hours in West RPJM are fairly spread out; at the highest demand hour the LMP is approximately $55 in Ohio Edison and $ 43 in East Kentucky. The median LMP is around $27. Overall, Central RPJM observes higher LMPs than West RPJM, which in turns observes higher LMPs than East RPJM in 2016.

Figure A.6: Day-ahead LMPs in West RPJM in 2016

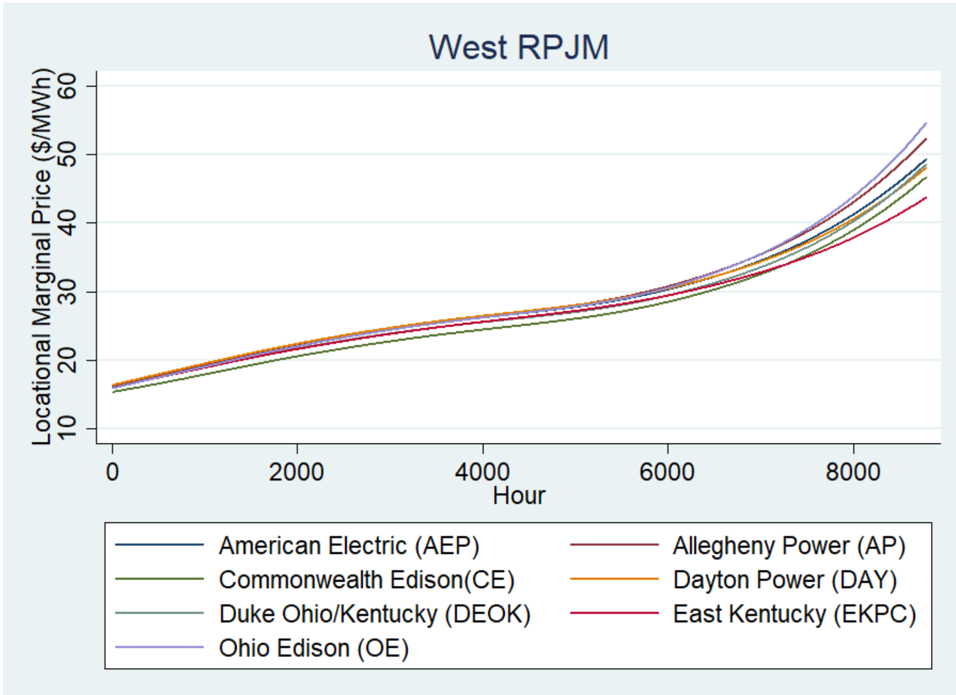
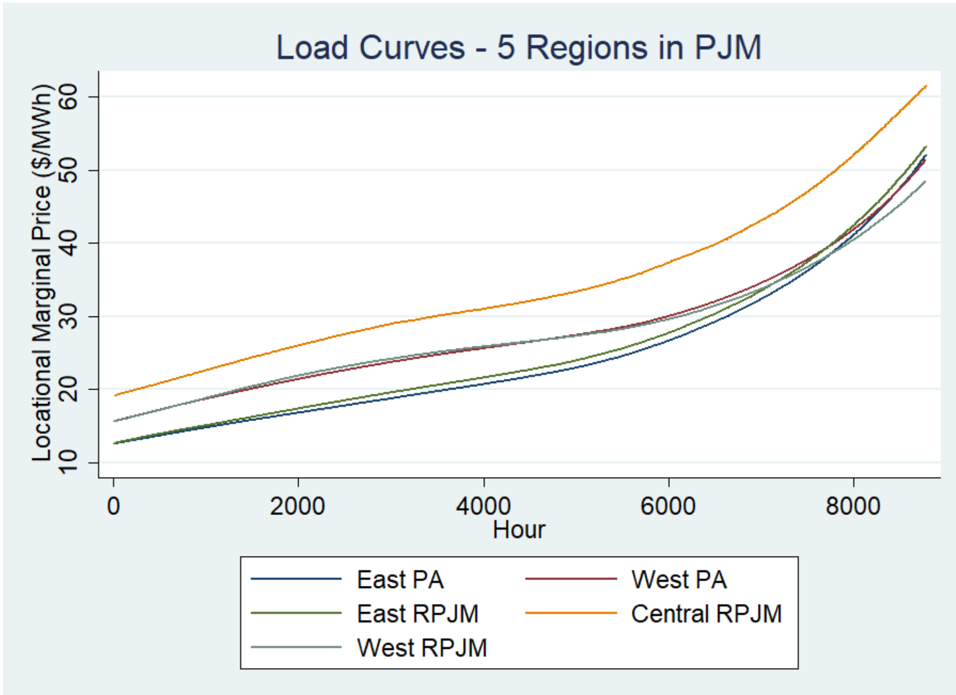


Figure A.7 summarizes the load weighted average day-ahead LMPs for the five PJM regions in RPAM, sorted from the lowest demand hour to the highest demand hour. Central RPJM has higher average LMPs in 2016 than all other regions. West Pennsylvania and West RPJM have the next highest average LMPs in low to moderate demand hours, followed by East Pennsylvania and East RPJM. While there appears to be some convergence—east and west–between Pennsylvania and RPJM at low and moderate demand hours, this breaks down in high demand hours. In higher demand periods West Pennsylvania observes higher average LMPs than West RPJM whereas East RPJM observes higher average LMPs than East Pennsylvania. In totum, in high demand hours, excluding Central RPJM, East RPJM has higher average LMPs, followed by East Pennsylvania, West Pennsylvania, and West RPJM. In general, the eastern part of PJM observes lower LMPs and overall is an exporter of electricity compared to the central and western parts of PJM.

Figure A.7: Load Weighted Average Day-ahead LMPs Across Five PJM Regions in 2016



Hourly metered load data for 2016 are taken from the dataset "Hourly Load: Metered" in PJM Data Miner 2.

3.1.2 Load Segments

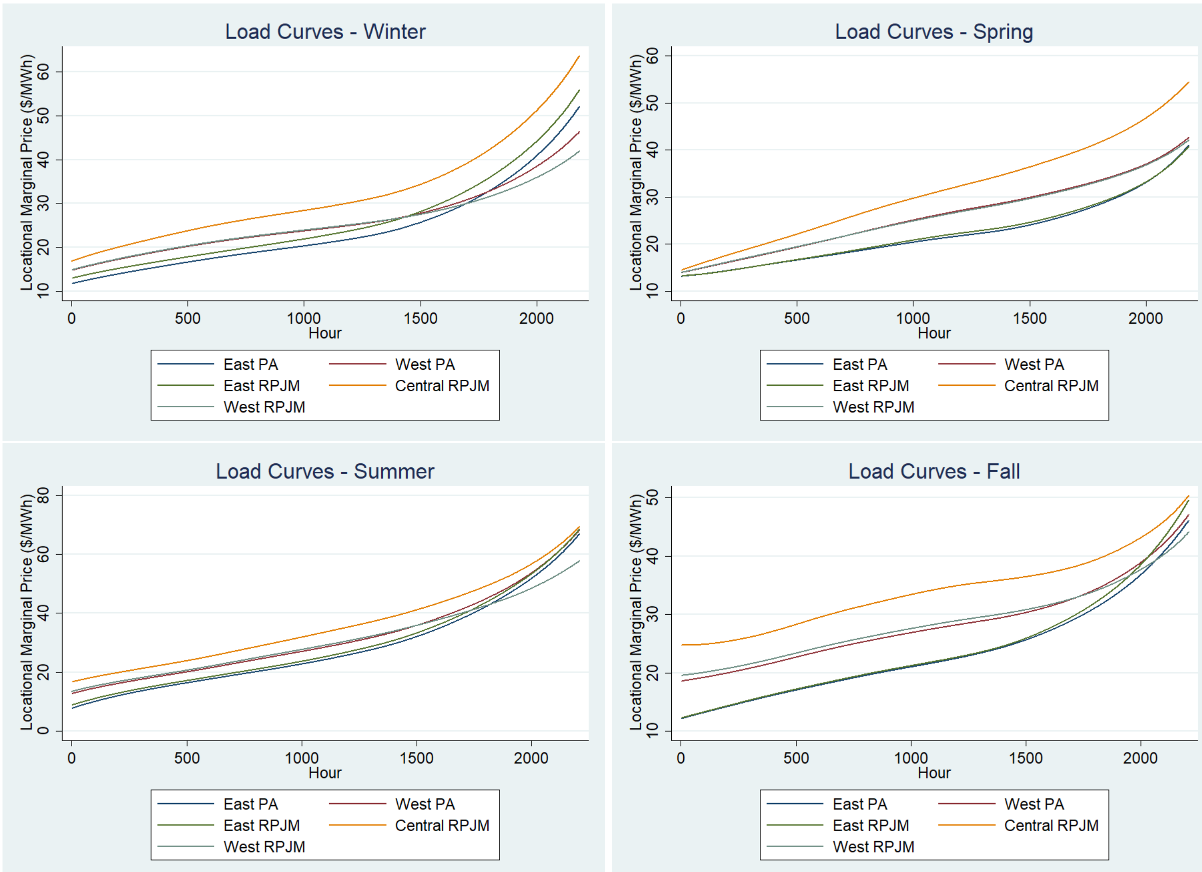
We consider 96 load segments consisting of representative hours that allow us to capture inter-temporal variability in demand across and within seasons and the correlation of demand with natural gas prices across time. To this end, we first divide the 8,784 hours in 2016 into four seasons: Winter (December 20 to March 21), Spring (March 22 to June 20), Summer (June 21 to September 20) and Fall (September 21 to December 21).

We next divide each season into six segments based on the the within season variation in demand across time. To do so, we use hourly day-ahead metered load data across all load zones in PJM in 2016 (*Hourly Load: Metered for 2016, PJM Data Miner 2: //dataminer2.pjm.com/feed/hrl_load_metered*, accessed 05/15/2017). We first sum hourly day-ahead metered load data across all load zones in PJM. We then sort total hourly PJM load from lowest to highest across the number of hour within each season to construct the Load Duration Curve. The first segment is defined as all hours that are within the top 1% of total PJM load. The second segment is defined as all hours between the 2nd and 5th percentiles of total PJM load. The third segment is defined as all hours between the 6th and 15th percentiles of total PJM load. The fourth segment is defined as all hours between the 16th and 45th percentiles of total PJM load. The fifth segment is defined as all hours between the 46th and 75th percentiles of total PJM load. Finally, the sixth segment is defined as all hours between the 76th and 100th percentiles of total PJM load. The construction of these six segments is consistent with IPM (2013), although here we consider four seasons and not two.

Finally, we further divide each of these 24 segments into four. To do so, we sort the PJM average hourly natural gas spot price from lowest to highest within each of the 24 prior segments. The first segment is defined as those hours in the 10% highest prices. The second load segment is defined as those hours with prices between the 11th and 30th percentiles. The third load segment is defined as those hours with prices between the 31st and 60th percentiles. Finally, the fourth load segment is defined as those hours with prices between the 61st and 100th percentiles. The PJM average hourly natural gas spot price is derived from the PJM average daily natural gas spot price, assuming that all hours within a day observe the same price. The PJM average daily natural gas spot price equals the average across all existing natural gas EGU's within PJM of the daily natural gas spot price spatially linked to that EGU, which is discussed in complete detail in Appendix Section **??**. This many-to-one correspondence between hours and load segments is used across all years.

Given the final construction of the 96 segments, we count the number of hours within each segment which equals δ_l. Figure A.8 depicts the hours within each season sorted from lowest to highest load-weighted average Locational Marginal Price in 2016, the latter which is calculated as described in the previous section. As expected, Summer has the highest LMPs, followed by Winter. Spring and Fall are shoulder months and thus have lower LMPs.

Figure A.8: Day Ahead Locational Marginal Prices in PJM in 2016



3.1.3 Slope and Intercept of Inverse Demand

We select n_{il} and c_{il} using an iterative process that relies on several full model solutions and which allows us to replicate the quantity demanded and the own-price elasticity of demand in region i and load segment l with high precision. In the first iteration, we obtain a solution to the full model assuming that demand is perfectly inelastic at the observed 2016 aggregate demand levels, L_{il}, for the regions and load segments defined above. This returns our first predicted value of the Locational Marginal Price (LMP) in region i at load segment l, LMP_{il}, conditional on the assumption of perfectly inelastic demand. Using this we then select n_{il} and c_{il} as follows:

$$n_{il} = \left(1 + \frac{1}{\eta_{il}^D}\right) LMP_{il}, \text{ and}$$
$$c_{il} = \left(\frac{1}{\eta_{il}^D}\right)\left(\frac{LMP_{il}}{L_{il}}\right), \tag{17}$$

where η_{il}^D is the own-price elasticity of electricity demand for region i and load segment l. We then re-run the full model assuming elastic demand reflecting the n_{il} and c_{il} selected above to obtain a more accurate prediction of LMP_{il} that is consistent with our calibrated demand elasticity. This new prediction is then used to select our final n_{il} and c_{il} following (17), which both replicates our baseline aggregate demand levels and the own-price elasticity of demand with only trivial numerical error remaining. Following Bushnell et al. (2017), which assumes very inelastic electricity demand and thus sets the slope of the demand curve so that the median elasticity in each region in their model is -0.05, we select $\eta_{il}^D = -0.05$ for all i and l. Inelastic electricity demand assumption is also support by Ito (2014), which estimates the values of electricity demand to be less than 0.10.

Following the same procedure outlined above for 2016, we also calibrate n_{il} and c_{il} for 2017 using the same elasticities, 2017 day-ahead LMPs (*Day-Ahead Hourly LMPs for 2017, PJM Data Miner 2*, accessed 03/21/2018), and 2017 load data (*Hourly Load: Metered for 2017, PJM Data Miner 2*, accessed 03/21/2018).

3.2 Supply of Electricity from Existing Generation

To calibrate the supply of existing generation in 2016, we use a multi-step approach. First, as described in Section 3.2.1, we aggregate $k = 1, ..., 3,095$ electric generation units (EGUs) in PJM into 843 representative EGUs based upon similarity in: location (state and load region), fuel type, heat rate, CO_2 emissions rate, and marginal costs. Second, as described in Section 3.2.2, we estimate m_{jl}^E and b_{jl}^E for each representative EGU based on the $k(j) \in \mathcal{J}_j$ subset of EGUs in the full sample that are aggregated to construct each representative EGU j. Finally, as described in Section 3.2.3, we obtain the remaining parameters, aggregated effective capacity K_{jl}^E, average EGU-level emission rate $\phi_{jl}^{E,P}$, and average EGU-level heat rate ψ_j.

3.2.1 Construction of Population of Existing EGUs

To construct the population of 3,095 existing EGUs in PJM in 2016, we use five different datasets: The National Electric Energy Data System (NEEDS) dataset version 5.13 (updated in

August 2015) (accessed 05/21/2017), the SNL dataset (accessed 05/21/2017), the EPA's Emissions & Generation Resource Integrated Database (eGrid 2014) (accessed 06/15/2017), the Continuous Emission Monitoring System dataset (CEMS) published by the Environmental Protection Agency (EPA) (accessed 06/28/2017) and Form EIA-923, which is a survey form collecting detailed electric power data on electricity generation, fuel consumption, fuel,... from power plants, (Schedules 3A & 5A - generator data including generation, fuel consumption and stocks) (accessed 07/18/2017), all of which are for the PJM control area. The reason we need all five datasets to create a full PJM generation dataset is because each dataset has its own shortcomings: The NEEDS dataset does not have updated with the newly added EGUs, the SNL dataset does not have information on locations of the EGUs, eGrid was last updated in 2014 by the time we last accessed it and thus does not have the most up-to-date data on all PJM EGUs, EIA-923 only includes a subset of PJM EGUs taken from a randomized procedure, and CEMS only includes EGUs of bigger size that are dispatched during the year. Our general method to establish a full PJM generator dataset is to first merge the NEEDs dataset and the SNL dataset to get the first version of the final dataset. Second, we manually check the plants which are in counties that we think might not be in PJM and remove them from this final dataset if necessary. Then, EIA-923 form, eGrid and CEMS datasets are used to match the plants in the final dataset to reasonable heat rates, capacities and emission rates.

The final NEEDS dataset that is used here consists of both active plants and retired plants and covers 10 NERC regions that roughly coincide with the PJM control area as of 2016: *PJM_AP*, *PJM_ATSI*, *PJM_COMD*, *PJM_DOM*, *PJM_EMAC*, *PJM_PENE*, *PJM_SMAC*, *PJM_WMAC*, *PJM_West*, and *S_C_KY*. The NEEDS dataset includes plant names, plant types, unit IDs, oris plant codes (Office of Regulatory Information System codes, which are the unique identifiers assigned to power plants in NEEDS), geographical locations of the plants at county level, fuel types, plant capacities, heat rates, and plants' available information (online years, retirement years). The SNL dataset includes plant names, plant types, unit IDs, plant capacities, fuel types, net annual CO_2 emissions, net annual generations, fuel costs and variable operation & maintenance costs (VOM costs). The NEEDS dataset is slightly out of date compared to the SNL dataset, so we combined it to the SNL dataset to obtain a final dataset that will be used for our model calibration. The final dataset consists of the active units located in counties of PJM control area that are in both NEEDS and SNL and the active units that are in NEEDS but not in SNL and those that are in SNL but not in NEEDS.

The NEEDS dataset has 3,071 units in total and the SNL dataset has 3,522 units in total. Most of the plant names, plant types, capacities and unit IDs in the two datasets are similar but not quite exactly the same, therefore, to find the matched and unmatched units in both datasets, we have to merge the two datasets multiple times using both regular merge (merge based on perfectly matched plant names, plant types and unit IDs) and probabilistic merge (merge based on similar plant names, plant types and unit IDs). We first find all the one-to-one unit matches, remove them from the NEEDS and SNL and then find the one-to-many, many-to-one, and many-to-many unit matches from the remaining units in both datasets. These non one-to-one matches occur because in some cases, the NEEDS report aggregate units made up of multiple boilers of the same plant types while the SNL reports each individual boilers. After finding all these matches, the leftover units from both datasets are the unmatched units, of which only those that are active, are included in the final dataset. Detailed processes of the one-to-one units matching and non-one-to-one units matching are described in the following subsections. Table A.1 and Table A.2 are summaries of our merge results for the NEEDS and the SNL.

One-to-One Matching NEEDS and SNL Units

To find one-to-one unit matches between NEEDS and SNL, we merge the two datasets four times. First, we match the units that have exactly the same plant names, plant types and unit IDs in NEEDS and SNL. This merge results in 456 one-to-one matched units between the two datasets. These matched units are set aside and removed from the original NEEDS and SNL datasets, leaving the remaining NEEDS dataset to now have 2,615 units and the SNL dataset to now have 3,066 units. Second, for the remaining units in the two datasets, we use a probabilistic merge (reclink2) in Stata, again using plant names, plant types and unit IDs with the additional requirement that unit IDs be matched exactly. The probabilistic merge gives us a match score for each unit in a range from 0 (not a match at all) to 1 (a perfect match). A match score of 0.9 or above provides a pretty good one-to-one match between the two datasets. We hand check those with a match score of less than 0.9 to filter out the wrong matches.

To do hand-checking, we consider a unit in NEEDS a match for a unit in SNL if they have similar plant names, the exact same unit ID, similar plant type, similar fuel type and similar capacity. For example, unit "Homer City" in SNL with plant type of Steam Turbine, unit ID of 2, fuel type of Coal and capacity of 617.5 MW is a one-to-one match for unit "Homer City Station" in NEEDS with plant type of Coal Steam, unit ID of 2, fuel type of Bituminous and capacity of 614 MW. This provides another batch of 1,577 one-to-one matched units. We again remove these additional one-to-one matched units from the two datasets.

Third, for the remaining units from the two datasets (1,038 units from NEEDS and 1,489 units from SNL), we again use reclink2, this time only using plant names and unit IDs as identifiers since the plant capacities for this subset of units maybe different. We notice several instances where an unit in SNL matches with more than one unit in NEEDS or several units in SNL match with one unit in NEEDS or several units in SNL match with several units in NEEDS. For example, unit "Covanta Plymouth (Montenay Montgomery)" in SNL with fuel type of Biomass, unit ID of 1 and capacity of 28 MW is a match for two units in NEEDS combined, which are "Montenay Montgomery LP" unit ID of 1 and unit ID of 2 with fuel type of Municipal Solid Waste (MSW), capacity of 14 MW each. But these types of matching units are not one-to-one matches and thus we rule them out for now and will only match them in the next subsection. We also relax the requirement of exactly matched unit IDs since the two datasets can have different unit IDs to mean the same units; for example, unit 1 of the same plant in the NEEDS dataset has unit ID of GEN1 (generator 1) but in the SNL dataset has unit ID of BOIL1 (boiler 1). They, however, both mean the same unit (unit 1). Hand-checking and correcting the match results from this round of merge, we have another 263 one-to-one matched units, bringing the total one-to-one matched units so far to 2,296 units.

Last, for the remaining units in the two datasets (775 units from NEEDS and 1,226 units from

SNL), we use reclink2 once more, this time only using plant names. Hand-checking and correcting the match results again, we end up with another 147 one-to-one matched units, bringing the total one-to-one matched units so far to 2,443 units. The breakdown of these units and their total capacities are shown in Table A.1 and Table A.2, rows 2-6. Of these 2,443 units, 2,367 units are active in both datasets, 36 units are only active in NEEDs, 27 units are only active in the SNL and 13 units are inactive in both datasets. We only include those units that are active in SNL in the final dataset, which means only 2,394 (2,367+27) are included in the final dataset out of the 2,443 one-to-one matched units.

After completing the one-to-one units matching, we have 628 units in the NEEDS that cannot be matched one-to-one to the units in SNL and 1,109 units in SNL that cannot be matched one-to-one to units in the NEEDS. These two sets of units are next to be matched together either one-to-many, many-to-one or many-to-many.

Non-One-to-One Matching NEEDS and SNL Units

We also match several units in NEEDS to one unit in SNL, or one unit in NEEDS to several units in SNL, or many units in NEEDS to many units in SNL, as long as these matching units have the same plant names in both datasets. To do this, we find plants in NEEDS and SNL that have the same or similar plant names, same or similar plant types and the same or close to the same total capacity across all the units in the plants of the same fuel types. For example, two coal units in SNL, Joliet 29 unit 7 and unit 8 with capacity of 518 MW each, combined together is a many-to-many match for four bituminous units in NEEDS, Joliet 29 units 71, 72, 81, 82 with capacity of 259 MW each. We find 66 SNL units that can be matched to 118 NEEDS units that can be collapsed down to just 41 one-to-one common plants or common sub-plants of the same fuel types between the two datasets. The breakdown of these units and their total capacities are shown in Table A.1 and Table A.2, rows 7-11. Of these 41 common plants, 40 plants are active in both datasets, corresponding to 113 units in the NEEDS and 65 units in the SNL, 1 plant is active in NEEDS but inactive in the SNL, corresponding to 5 units in the NEEDS and 1 unit in the SNL. There is no units inactive in the NEEDS but active in SNL and no units inactive in both datasets.

We again only include those units that are active in SNL in the final dataset, which means only 65 additional units are included in the final dataset out of the 66 one-to-one matched units. Note that we only include the units from one dataset (SNL) to avoid double counting. We choose the SNL because random unit checks online show the SNL to have more accurate capacities.

We now have 2,509 units in SNL matching with 2,561 units in NEEDS. Removing these unit matches from the original NEEDS and SNL datasets, we end up with 510 unmatched units in NEEDS (Table A.2, row 12) (of which 240 units are retired) and 1,013 unmatched units in SNL (of which 23 units are retired) (Table A.2, rows 12-14).

Checking Unmatched NEEDS and SNL Units After matching is completed, there remain 270 active units in NEEDS that cannot be matched to the SNL. Since the NEEDS is slightly outdated compared to the SNL, it is possible some of the 270 units are already retired. We search each of these units on the web to remove those units that are no longer available as of 2016. Of these 270 units, we find 34 units are actually retired, closed, withdrawn, demolished, decommissioned, shuttered, forced to stop due to regulatory violations, or not yet operating in 2016, leaving us with only 236 active unmatched units in NEEDS. Of these 236 units, 53 are believed to be aggregated units over small capacity units of the same fuel types, regions and states.

We believe these 53 units are disaggregated in the SNL dataset and thus they are not included in the final dataset to avoid double-counting. Of the 183 remaining units, 62 are believed to not be actually in PJM since the 10 PJM NERC regions do not exactly match the PJM control area, 2 units had capacity of 0 and did not generate during 2016, 14 are small solar PV units, 24 (most of them are combustion turbine units) are small generators suspected to provide power to local facilities and non-dispatchable by PJM, 21 are small units of less than 3 MW that we cannot find information about operating status or capacities. We exclude these units mentioned above (34+53+62+2+14+24+21=210) from the final dataset. Therefore, only 60 units from the 270 unmatched units in the NEEDS are included in the final dataset (Table A.1, row 13). These are the units that are still operating and in PJM control area but are not in the SNL.

For the remaining unmatched units in SNL (1,013 units), we filter out the 23 units that are inactive and hand-check the remaining 990 units to make sure they are indeed in PJM control area. After manually checking these units, we only keep 576 units that we believe to belong in PJM and integrate these units into our final dataset (Table A.2, row 13).

Table A.1: NEEDS Dataset v5.15 Unit Breakdown.

	Number of Units	Nameplate Capacity of Units (MW)	Included in Final Dataset?
Total Number of Units in NEEDS v5.15 Dataset	3,071	219,511	—
One to One Matched with SNL Units	2,443	178,307	—
Active Units In NEEDS and SNL	2,367	173,503	Y
Active in NEEDS and Inactive in SNL	36	2,092	N
Inactive in NEEDS and Active in SNL	27	2,451	Y
Inactive in both NEEDS and SNL	13	261	N
Collapsed to Merge with SNL Units	118	5,308	—
Active Units In NEEDS and SNL	113	5,212	Y
Active in NEEDS and Inactive in SNL	5	96	N
Inactive in NEEDS and Active in SNL	0	0	Y
Inactive in both NEEDS and SNL	0	0	N
Unmatched with SNL	510	35,896	—
Units in PJM and Still Active, but Not in SNL	60	2,470	Y
Units Not Included in Final Dataset	450	33,426	N
Unmatched Aggregate Units	53	1,650	N
Not in PJM	109	11,908	N
In PJM	288	19,868	N
Listed As Inactive by NEEDS	202	16,865	N
Identified As Inactive Via Web Search	25	2,893	N
Otherwise Removed Via Web Search	61	109	N

Table A.2: SNL Dataset Unit Breakdown as of 2016.

	Number of Units	Nameplate Capacity of Units (MW)	Included in Final Dataset?
Total Number of Units in SNL Dataset	3,522	193,500	—
One to One Matched with NEEDS Units	2,443	176,635	—
Active Units In NEEDS and SNL	2,367	161,420	Y
Active in NEEDS and Inactive in SNL	36	11,643	N
Inactive in NEEDS and Active in SNL	27	2,266	Y
Inactive in both NEEDS and SNL	13	1,306	N
Collapsed to Merge with NEEDS Units	66	5,138	—
Active Units In NEEDS and SNL	65	4,771	Y
Active in NEEDS and Inactive in SNL	1	367	N
Inactive in NEEDS and Active in SNL	0	0	Y
Inactive in both NEEDS and SNL	0	0	N
Unmatched with NEEDS	1,013	11,727	—
Not in PJM	414	850	N
In PJM	599	10,877	—
Units Included in Final Dataset	576	10,646	Y
Units in SNL, Marked as Inactive	23	231	N

Final Dataset Unit Breakdown

After matching the NEEDs and the SNL, we have 3,509 units in total. Table A.3 summarizes the breakdown of these units and their total capacity (rows 2-4) as well as the breakdown of fuel types (rows 5-18). This dataset consists of the matched units that are active in both NEEDS and SNL or active in SNL and inactive in NEEDS and the unmatched units in SNL and in NEEDS. As mentioned earlier, of the matched units, 2,394 one-to-one matched units are added to the final dataset and additional 65 non-one-to-one matched units are also added in the final dataset, summing to 2,459 units. Finally, we also include the 60 unmatched units in NEEDS and the 576 unmatched in SNL in the final dataset.

All the units in this dataset make up total capacity of 181,573 MW, of which 168,457 MW are in both NEEDS and SNL, 2,320 MW are in NEEDS only and 10,796 MW are in SNL only. The biggest fuel sources are gas, coal and nuclear, with natural gas units make up 38% of total capacity in PJM, followed by coal units with 32% and nuclear units with 17%. Renewables units and oil units are only 9% and 4% of total PJM capacity, respectively. Biomass, landfill gas, and other fuel types are negligible, making up of only 1% of total capacity in PJM. The final dataset unit breakdown is shown in Table A.3.

Table A.3: Final Dataset Unit Breakdown in 2016.

	Number of Units	Nameplate Capacity of Units
Total Number of Units in Final Dataset	3,095	181,573
Included in both NEEDS and SNL	2,459	168,457
Included in NEEDS and Not Included in SNL	60	2,470
Not Included in NEEDS and Included in SNL	576	10,646
Natural Gas	836	68,688
Combustion Turbines	597	35,468
Combined Cycle	231	33,190
Other	8	30
Coal	181	57,359
Oil	548	7,023
Nuclear	32	31,244
Biomass & Landfill Gas	765	1,547
Renewables	723	15,479
Solar	340	1,544
Wind	78	5,317
Hydro	305	8,616
Other Fuel	10	233

3.2.2 Marginal Costs of Existing Generation

For each j, m^E_{jl} and b^E_{jl} are estimated using the following OLS regression:

$$b^E_{k(j)l} = m^E_{jl} K^E_{k(j)l} + b^E_{jl} + \epsilon^E_{k(j)l}, \tag{18}$$

where $b^E_{k(j)l}$ is total marginal costs of producing electricity from EGU $k\,(j)$ during load segment l, $K^E_{k(j)l}$ is the effective capacity of EGU $k\,(j)$ during any given hour in load segment l, and $\epsilon^E_{k(j)l}$ is the error term.

Effective capacity for each EGU k in the original sample and segment l is calculated as:

$$K^E_{k(j)l} = \tilde{K}^E_{k(j)} \gamma^E_{k(j)l}, \tag{19}$$

where $\tilde{K}^E_{k(j)}$ is the nameplate capacity for EGU $k(j)$ as described above and $\gamma^E_{k(j)l}$ is the capacity factor after adjustments for EGU $k(j)$ in segment l. For the subset of existing EGUs in the original sample that are in both the NEEDS and SNL datasets, we use the reported nameplate capacity reported in SNL whereas for those units that are in NEEDS but not in SNL, we use the reported nameplate capacities from NEEDS. We give preference to the nameplate capacities from SNL as the SNL dataset has been more recently updated.

The capacity factor after adjustments for EGU $k(j)$ in segment l equals: $\gamma_{kl}^{E} = \nu_{fuel(k)}\tilde{\gamma}_{kl}^{E}$, where $\nu_{fuel(k)}$ is the capacity factor scalar used to ensure that total capacity by fuel type $fuel\,(k)$ of unit k matches market monitor data and $\tilde{\gamma}_{kl}^{E}$ is the capacity factor of unit k in segment l given historical data on plant outages and maintenance. The capacity factor scalar is calculated as follows: $\nu_{fuel} = \frac{\tilde{K}_{fuel}^{E,M}}{\sum_{k(fuel)}\tilde{K}_{k}^{E}}$, where $\tilde{K}_{fuel}^{E,M}$ is the total capacity of fuel type $fuel$ in PJM as reported by Market Monitoring Analytics in their 2016 State of the Market Report (*PJM Installed Capacity by Fuel Type, Section 5 - Capacity Market, page 214, 2016 State of the Market Report for PJM*) and $k\,(fuel)$ denotes the subset of existing EGUs in the original sample with fuel type $fuel$.

The capacity factor of unit k in segment l given historical data on plant outages and maintenance is calculated as follows: $\tilde{\gamma}_{kl}^{E} = cf_{fuel(k)}^{E,M} pa_{fuel(k)l}$. $cf_{fuel(k)}^{E,M}$ is the capacity factor by fuel type in PJM in 2016 provided in the Market Monitoring Analytics' 2016 State of the Market Report (*Table 5-26 PJM capacity factor (By unit type (GWh): January through December, 2015 and 2016, Section 5 - Capacity Market, page 250, 2016 State of the Market Report for PJM*). $pa_{fuel(k)l}$ is the plant availability by fuel type in segment l. For EGUs whose fuel type is nuclear, $pa_{fuel(k)l} = (1 - nor_{kl})$, where nor_{kl} is the nuclear outrage rate, measured in percentage, for EGU k in load segment l, taken from the Energy Information Administration (EIA)'s Daily U.S. Nuclear Outage for 2016 (*status of US. Nuclear Outages, 2016://www.eia.gov/nuclear/outages/#/?day=1/1/2016*, accessed 05/21/2017) and then aggregated from daily outrage rate to outage rate by load segment. For EGUs whose fuel type is not nuclear, we calculate $pa_{fuel(k)l} = or_{kl}$, where or_{kl} is the non-nuclear plant outrage rate in 2016 for EGU k and load segment l, taken from the Generating Availability Data System (GADS) for 2016 (accessed 05/17/2017). Non-nuclear plant outage rate in GADS in by fuel type and by month, so assuming the same outage rate for non-nuclear fuel types in each hour of the same month, we calculate the percentage of outage for each fuel type in each load segment or_{kl}. The percentage of outage for each fuel type in each load segment in 2016 is kept constant for 2017 and later years.

Effective capacity for each EGU in 2017 is calculated the same way. Capacity factors for 2017 are taken from Market Monitoring Analytics' 2017 State of the Market Report (*Table 5-31 PJM capacity factor (By unit type (GWh)):2016 and 2017, Section 5 - Capacity Market, page 277, 2017 State of the Market Report for PJM*).

$b^{E}_{k(j)l}$, the total marginal cost of producing electricity from existing EGU k during load segment l, is calculated as follows:

$$b^{E}_{k(j)l} = \left(\frac{1}{1000}\right) \psi^{E}_{k(j)} \left[p^{E,fuel}_{k(j)l} + p^{E,SO_2} r^{E,SO_2}_{k(j)} + p^{E,NOx} r^{E,NOx}_{k(j)}\right] + VOM^{E}_{k(j)} \tag{20}$$

where $\psi^{E}_{k(j)}$ is the heat rate of existing EGU $k\,(j)$, originally measured in BTU/kWh. And thus, $\left(\frac{1}{1000}\right) \psi^{E}_{k(j)}$ is the heat rate of existing EGU $k\,(j)$ measured in $mmBTU/WWh$. $p^{E,fuel}_{k(j)}$ is the delivered fuel price of existing EGU $k\,(j)$ of fuel type $fuel$, measured in $\$/mmBTU$. p^{E,SO_2} and $p^{E,NOx}$ are the SO_2 and NOx allowance price for that year (in $\$/lb$) for existing $\mathrm{SO_2}$ and NOx emitting EGUs, taken from EIA (*2016 SO_2 Allowance Auction, Clean Air Markets, EIA: https://www.epa.gov/airmarkets/2016-so2-allowance-auction*). $r^{E,SO_2}_{k(j)}$ and $r^{E,NOx}_{k(j)}$ are $\mathrm{SO_2}$ and NOx allowance rates, measured in $lbs/mmBTU$ for existing EGU $k\,(j)$. For existing EGUs that are in NEEDS, their SO_2 and NOx allowance rates, $r^{E,SO_2}_{k(j)}$ and $r^{E,NOx}_{k(j)}$, are taken from NEEDS. For those EGUs that are not in the NEEDS, we calculate their SO_2 and NOx allowance rates as the average SO_2 and NOx allowance rates of the SO_2 and NOx allowance rates of all the EGUs in the states that they are located in. And finally, $VOM^{E}_{k(j)}$ is the variable operation and maintenance cost of producing 1 MWh from existing EGU $k\,(j)$, measured in $\$/MWh$, taken from the SNL dataset, for those EGUs that are in SNL. For those EGUs that are not in SNL, we calculate their $VOM^{E}_{k(j)}$ as the average $VOM^{E}_{k(j)}$ of the EGUs of the same fuel type in the same state. We discuss the data sources and imputation of heat rate $\psi^{E}_{k(j)}$ and delivered price price $p^{E,fuel}_{k(j)}$ below.

Heat rate: We assign each existing EGU, $k\,(j)$, in our final dataset its heat rate, $\psi^{E}_{k(j)}$, using five datasets: CEMS, eGrid, SNL, EIA form 923 and NEEDS. We start with the EGUs that are in CEMS because CEMS collects actual emission rates and heat rate reported by EGUs that are dispatched by PJM in 2016. First, we use heat rates from CEMS for EGUs in the final dataset that are also in the CEMS in 2016 (374 units). Second, we assign the remaining 2,721 EGUs (3,095-374) heat rates from eGrid as long as the heat rates in eGrid that correspond with these EGUs are not above 42,545.31 BTU/kWh, which is eGrid's average heat rate plus two times its standard deviation (13,147.53 + 2(14,698.89)) and as long as the corresponding EGUs in eGrid are not marked "Data from EIA-923 Generator File overwritten with distributed data from EIA-923 Generation and Fuel". We do this to avoid assigning unrealisticly high heat rates to EGUs in our final dataset (due to reporting errors on eGrid) and to avoid assigning heat rates from EGUs in eGrid that report negative total generations, which coincide with the EGUs that are marked "Data from EIA-923 Generator File overwritten with distributed data from EIA-923 Generation and Fuel". After this step, 1,490 additional EGUs from the final datasets are assigned heat rates.

We assign the remaining 1,231 EGUs (2,721-1,490) their heat rates from SNL, as long as the heat rates in SNL that correspond with these EGUs are not above 26,473.842 BTU/kWh, which is SNL's average heat rate plus two times its standard deviation (8,914.102+2*8,779.87). Since the SNL performs their own heat rate calculation using EIA form 923, in some cases when some EGUs generate a very small amount of electricity throughout the entire year, their estimates of heat rates for these units are so unrealistically high that they have to cap them at 100,000 BTU/kWh. We believe these estimates are not reasonable and want to exclude these EGUs from our heat rate calculation. Therefore, we establish the heat rate threshold of 26,473.842 BTU/kWh and only assigned SNL's EGUs with heat rates below these threshold to EGUs in our final dataset. After this step, we assign heat rates to additional 801 EGUs in our final dataset.

To assign heat rates to the remaning 430 EGUs (1,231-801), we use the EIA 923 form, which reports heat rates for a subset of these 430 EGUs (411) for five years 2012-2016. We calculate the average heat rate across five years and assign them accordingly to these 411 EGUs. Finally, the 19 remaining EGUs (430-411) are assigned heat rates from the NEEDS. Summary of heat rate assignment is shown in Table A.4.

Table A.4: Heat Rate Assignments to Units in Final Dataset.

Dataset	Number of Units Assigned Heat Rate to
Final Dataset	3,095
CEMS	374
eGrid	1,490
SNL	801
EIA 923	411
NEEDS	19

Delivered Fuel Prices: We obtain delivered prices for different fuel types, $p_{k(j)}^{E,fuel}$, for existing EGUs $k(j)$, from two sources: Bloomberg Terminal and the Energy Information Administration (EIA).

Natural Gas Prices: To obtain natural gas prices for all gas-fired EGUs in our PJM final dataset, we use *Daily Natural Gas Spot Pice from Bloomberg Terminal* for seven gas hubs: Alliance, Dominion North Point, Chicago City Gate, Lebanon OH, TETCO Zone M3, Tennessee Gas Zone 4 - Marcellus and Transco Leidy in 2016. Assuming that each EGU from our final dataset purchases natural gas from the hub that is closet to its location in 2016, we map these hubs and these EGUs in GIS and assign each EGU that has geographical coordinate data to the gas hub closest to it. We assume EGUs purchase natural gas from the same gas hubs in 2017 and 2018 and in later years. For the gas-fired EGUs in our final dataset that do not have data on geographical coordinates, we assign them the average daily natural gas spot prices of all the gas-fired EGUs in the states that they are located in.

To calculate gas transportation price, we use natural gas delivered price to the electric power sector from the EIA's Annual Energy Outlook (AEO) 2017 (*Table: Energy Prices by Sector and Source, Case: Reference case, AEO 2017*) for 2016 prices by census region and aggregate the Bloomberg Terminal's natural gas spot prices above also by census region. The gas transportation price for each census region is then determined by subtracting the aggregated regional Bloomberg Terminal's natural gas spot prices from the natural gas delivered price in that region in 2016.

The final natural gas fuel price for each natural gas-fired EGU is determined by summing the natural gas spot price from the hub that is assigned to that EGU with the transportation cost to the census region in which the EGU is located.

The PJM daily natural gas spot prices as used in section 3.1.2 to establish PJM's load segments, are calculated as the average of all the daily natural gas spot prices from all the gas-fired EGUs in PJM in each load segment.

Coal Prices: To obtain coal spot prices for coal-fired EGUs in our PJM final dataset, we use weekly coal spot prices for five main coal basins in 2016 from the EIA (*Coal markets archive, EIA://www.eia.gov/coal/markets/*): Central Appalachia Basin, Northern Appalachia Basin, Illinois Basin, Powder River Basin and Unita Basin. Coal transportation prices from each coal basin to the states that it historically shipped to are taken from the EIA's Coal Transportation Rates to the Electric Power Sector database for different types of transportation modes - by railway (*Table 3c. Average annual coal transportation costs from coal basin to state by railroad, Coal Transportation Rates to the Electric Power Sector, EIA*), by truck (*Table 3a. Average annual coal transportation costs from coal basin to state by truck, Coal Transportation Rates to the Electric Power Sector, EIA*), and by waterway (*Table 3b. Average annual coal transportation costs from coal basin to state by waterway, Coal Transportation Rates to the Electric Power Sector, EIA*). The transportation prices are then weight averaged in each PJM region by the modes of transportation above. We then calculate weekly total coal prices for coal-fired EGUs in our dataset assuming these coal-fired EGUs potentially buy coals from the five basins by adding the weekly coal spot prices from the respective basin to the weighted coal transportation price from that basin to the state in which the EGUs are located. Next, we average these five total coal prices from five basins by load segments to get the five potential total coal prices for coal-fired EGUs by each segment. The final total coal price for each coal-fired EGU in each load segment is then determined by the minimum total coal price for that EGU in that load segment.

Oil Prices and Nuclear Prices: We obtain annual delivered distillate oil prices and uranium prices for electric power sector by census region for 2016 from the EIA's Annual Energy Outlook 2017 (*Table: Energy Prices by Sector and Source, Case: Reference case*).

Other Fuel Prices: Other fuel prices (biomass and other fuels) are taken from SNL power plant data, associated with each EGU.

3.2.3 Construction of Population of Existing Aggregate EGUs

To construct the population of existing aggregate EGUs that are finally used in RPAM, the next step is to group these 3,095 existing EGUs $k(j)$ established in previous section into bins (aggregate EGUs) j of the same or similar attributes. These attributes include total marginal cost, fuel type, emission rate, heat rate and location by state s and region i. After this binning process, we reduce 3,095 existing EGUs in our final EGU dataset to 843 aggregate EGUs. Parameters of these 843 EGUs are constructed as follows.

Effective Capacities of Aggregate EGUs: The effective capacity K^E_{jl} of each aggregate EGU j, as shown in equation (3), is the sum of all the effective capacities $K^E_{k(j)}$ of all EGUs $K^E_{k(j)}$ of aggregate bin/EGU j in load segment l, as established in section 3.2.2 above:

$$K^E_{jl} = \sum_{k(j)} K^E_{k(j)l}, \tag{21}$$

Heat Rates and Emission Rates of Aggregate EGUs: Heat rate ψ^E_j and CO_2 emission rate ϕ^{E,CO_2}_j for each of the 843 aggregate EGUs is calculated by averaging heat rates $\psi^E_{k(j)}$ and emission rates $\phi^{E,CO_2}_{k(j)}$ of all the existing EGUs $k(j)$ that make up this aggregate EGU j:

$$\psi^E_j = \frac{\sum_{k(j)} \psi^E_{k(j)}}{N_{k(j)}} \tag{22}$$

$$\phi^{E,CO_2}_j = \frac{\sum_{k(j)} \phi^{E,CO_2}_{k(j)}}{N_{k(j)}} \tag{23}$$

where $N_{k(j)}$ is the number of EGU $k(j)$ in aggregated EGU (bin) j.

CO_2 emission rates $\phi^{E,CO_2}_{k(j)}$ of all the existing EGUs $k(j)$ in the final dataset are detailed below in section 4.

Construction of Supply Curves of Aggregate EGUs: After establishing the total marginal cost $b^E_{k(j)l}$ of each EGU $k(j)$ at load segment l and its effective capacity $K^E_{k(j)l}$, we perform OLS regressions of $b^E_{k(j)l}$ on $K^E_{k(j)l}$ for all EGUs $k(j)$ that make up bin/aggregate EGU j. The fitted slopes and intercepts of these regressions are m^E_{jl} and b^E_{jl}, as shown in equation (18).

3.3 New Capacity and Supply of Electricity from New Generation

We assume that when new capacity $\bar{K}^N_j$, measured in MW, of new EGU j is added in a given year, it supplies electricity of g^N_{jl} MWh in a representative hour in load segment l, at constant private marginal costs b^N_{jl} and it is expanded with capital costs C^N_j.

There are three possible technologies whose capacities can be added each year in each state in our model: NGCC, wind, and solar. These are the technologies that are most likely to be developed due to low gas prices and increase in demand for clean energy. We assume the average utilization factors across all new NGCC, wind and solar EGUs in our model in 2016 for these technologies. Specifically, using data for utilization factor by fuel type in PJM published by the Monitoring Analytics in their 2016 State of the Market Report, the assumed utilization factor γ^N_j for a new NGCC EGU is 0.961, for a new wind EGU is 0.295, and for a new solar EGU is 0.17. We also assume that the new wind and solar generations within each state are available to be used to satisfy the RPS requirements for that state, and that the new NGCC generations are covered generations under RGGI if the states they are in are RGGI participating states.

The total private marginal operating cost for a new EGU j in a representative hour of load segment l, b^N_{jl}, is calculated as:

$$b^N_{jl} = \left(\frac{1}{1000}\right)\psi^N_j\left[p^{N,fuel}_{jl} p^{N,SO_2} r^{N,SO_2}_j + p^{N,NOx} r^{N,NOx}_j\right] + VOM^N_j \tag{24}$$

where ψ^N_j is the heat rate of new EGU j, originally measured in BTU/kWh. And thus, $\left(\frac{1}{1000}\right)\psi^N_j$ is the heat rate of existing EGU j measured in mmBTU/WWh. For new wind and solar EGU, $\psi^N_j = 0$ and for new NGCC EGU, ψ^N_j is the average of the heat rates of all existing NGCC EGUs in PJM, which is equal to 9000 BTU/KWh (after a little rounding). $p^{N,fuel}_{jl}$ is the delivered fuel price of new EGU j of fuel type $fuel$ in a given hour in load segment l, measured in \$/mmBTU.

For new wind and solar EGU, $p_{jl}^{N,solar} = p_{jl}^{N,wind} = 0$, and for new NGCC EGU, $p_{jl}^{N,gas}$ is equal to the average $p_{k(j)l}^{E,gas}$ of all existing NGCC EGUs in the same state in load segment l. p^{N,SO_2} and $p^{N,NOx}$ are the SO_2 and NOx allowance price for that year (in $/lb) and thus they are the same as allowance price for existing $\mathrm{SO_2}$ and NOx emitting EGUs for that year. r_j^{N,SO_2} and $r_j^{N,NOx}$ are $\mathrm{SO_2}$ and NOx allowance rates for new NGCC EGU j, measured in lbs/mmBTU, calculated as the average SO_2 and NOx allowance rates of the SO_2 and NOx allowance rates of all the existing NGCC EGUs in the states that they are located in. And finally, VOM_j^N is the variable operation and maintenance cost of producing 1 MWh from new EGU j, calculate as the average $VOM_{k(j)}^E$ of the existing EGUs of the same fuel type in the same state.

Capital costs C_j^N for the three technologies for the 2017 baseline are determined by solving the combined error minimization problem in which the error is the sum of the net difference between the actual capacities expanded by technology for PA and RPJM in 2017 and the model's predicted capacities expanded by technology for PA and RPJM, and the net difference between the actual emission weighted REC prices and the model's emission weighted REC prices in PA and RPJM, choosing C_j^N the marginal capital cost for new NGCC, solar and wind EGUs in PJM, and γ_q, the percentage of total amount of external RECs that all external EGUs q can supply to states in PJM. Data from new capacities in PJM are taken from PJM's *New Service Queue database: //www.pjm.com/planning/services-requests/interconnection-queues.aspx, accessed 03/21/2018.* In 2017, there were 1,340 MW of new natural gas capacity, 0 MW of new wind capacity and 0 MW of new solar capacity in PA. In the same year, RPJM states observed 1,626 MW of new natural gas capacity, 126 MW of new wind capacity and 204 MW of new solar capacity. Data for actual REC prices are taken from SN's Market Intelligence (California Carbon/RGGI Allowances report://platform.marketintelligence.spglobal.com/web/client?auth=inherit#markets/co2AndRGGIAllowances, accessed 02/19/2018).

Analytically, the error minimization is as follows:

$$loss^{cap-rec} = \min_{C_j^N, \gamma_q^{PA}, \gamma_q^{RPJM}} \left(\left| \bar{K}_j^{N,PA} - \hat{K}_j^{N,PA} \right| + \left| \bar{K}_j^{N,RPJM} - \hat{K}_j^{N,RPJM} \right| \right.$$
$$\left. + \sum_t \left| p_t^{r,PA} - \hat{p}_t^{r,PA} \right| + \sum_t \left| p_t^{r,RPJM} - \hat{p}_t^{r,RPJM} \right| \right) \qquad (25)$$

where C_j^N are the calibrated marginal capital costs for new EGU of technology type j in PJM, γ_q^{PA}, γ_q^{RPJM} are the percentages of the total amounts of external RECs that an external EGU q can provide to Pennsylvania or RPJM states, $\bar{K}_j^{N,PA}$, $\bar{K}_j^{N,RPJM}$ are the actual total capacities of technology j being expanded in Pennsylvania and Rest of PJM, $\hat{K}_j^{N,PA}$, $\hat{K}_j^{N,RPJM}$ are the model's predicted the total capacities of technology j being expanded in Pennsylvania and Rest of PJM, $p_t^{r,PA}$, $p_t^{r,RPJM}$ are the actual generation weighted REC prices by tier t in Pennsylvania and Rest of PJM, and $\hat{p}_t^{r,PA}$ and $\hat{p}_t^{r,RPJM}$ are the model's predicted generation weighted REC prices by tier t in Pennsylvania and Rest of PJM.

The solution to the optimization problem above gives us the calibrated marginal capital costs for new NGCC, wind, solar EGUs in PJM, assuming these marginal capital costs by fuel type are the same across all states in PJM, C_j^N, and the percentage of external RECs that each external EGU q can supply RECs to Pennsylvania or Rest of PJM, γ_q^{PA} and γ_q^{RPJM}. In 2017 in PJM, the marginal capital cost for expanding 1 MW of new NGCC capacity is \$73,900, of new wind capacity is \$135,580 and of new solar capacity is \$135,000. In 2017, $\gamma_q^{PA} = 0.615$ and $\gamma_q^{RPJM} = 0.71$. We discuss more about external RECs in the next section, section 3.4.

3.4 External RECs

We allow for import of external RECs from outside of PJM to help PJM states comply with their RPS targets. Data of external EGUs that are eligible to provide RECs to PJM States are taken from PJM Environmental Information Services (EIS)'s tracking system Generation Attribute Tracking System (PJM-GATS) for nine states: District of Columbia, Delaware, Illinois, Maryland, New Jersey, Ohio, Pennsylvania, Virginia, and West Virginia. EGUs that are eligible to provide RECs to North Carolina and Michigan are not tracked in PJM-GATS but in their own tracking systems: The North Carolina Renewable Energy Tracking System (NC-RETS) for North Carolina, and the Michigan Renewable Energy Certificates System (MIRECS) for Michigan. By the end of 2017, there are in total 262 units outside of PJM that are eligible to supply RECs to states in PJM.

Since not all of the RECs supplied by these 262 external EGUs are used by PJM states to satisfy their RPS targets, we also limit number of total RECs that can be imported into PJM so that our model's generation weighted REC prices match well with actual generation weighted REC prices in Pennsylvania and Rest of PJM in 2017. This results in allowing only 61.5% of the RECs that are eligible to be imported to Pennsylvania to actually be able to be bought by Pennsylvania, and only 71% of the RECs that are eligible to be imported to Rest of PJM to be able to be bought by Rest of PJM states. These percentages are the results of a calibrated process mentioned in section 3.3 above. In other words:

$$\gamma_q = \begin{cases} 0.615, & \text{if EGU q is eligible to provide RECs to PA} \\ 0.710, & \text{if EGU q is eligible to provide RECs to RPJM} \end{cases} \tag{26}$$

3.5 Transmission Network

Transmission line data are taken from SNL's *Operating Transmission Projects Map* for 2016. Transmission lines that connect every two zones within two PJM regions are aggregated into single aggregated transmission lines, which reflect the net maximum MWhs that can be transferred in between two PJM regions, as shown in Figure $A.1$. We consider a line to connect between two regions if it connects two ISO market hubs, one in each region. We have in total five aggregated transmission lines among our five PJM regions. The table below shows the five aggregate links among our five LMP regions and their respective aggregate KV.

Table A.5: PJM Transmission Networks

Transmission Line Between	Total KV (KV_i)
PA East and PA West	960
PA East and RPJM East	1,880
PA East and Central RPJM	690
PA East and RPJM West	N/A
PA West and RPJM East	N/A
PA West and Central RPJM	N/A
PA West and RPJM West	5,208
RPJM East and Central RPJM	N/A
RPJM East and RPJM West	N/A
Central RPJM and RPJM West	3,460

To know the actual transmission capacities of these lines in MWh, we are still missing the electric current of each line above, which is the aggregation of all individual lines between every two PJM regions. Therefore, there is no one realistic current we can assume for each aggregate transmission line. We also do not observe the true transmission capacities which can vary in real time due to many climate factors such as temperature, solar radiation, wind speed and direction, etc... Furthermore, our model is an aggregate model and our objective is to calibrate average congestion LMPs for the five links above, simply adding the transmission capacities between PJM regions does not capture well these aggregate price effects as the true congestion LMPs reflect complicated grid realities such as the complicated and largely unobserved dis-aggregated transmission system between zones within PJM regions which may vary across seasons and correlate with load. As a result, to calibrate these five aggregate transmission line capacities in MWh, we search for the optimal values of five scalers in each load segment ($\hat{A}_{il}$), with which $\bar{f}_{il} = (1,000)(V_i)\hat{A}_{il} = (KV_i)\hat{A}_{il}$ represents the transmission capacity in each representative hour in load segment l that minimizes the LMP congestion loss function across PJM in that load segment l, using a method similar to the one used in Ferreyra (2007).

By performing a grid search of 100,000 iterations of combinations of scalers, $\hat{A}_{il}$, among the five LMP regions in the range of 0.2 to 2, with increment of 0.2, similar to Ferreyra (2007), in the first stage, we find the optimal model's predicted congestion LMPs in 5 PJM regions, $prLMP_{ilc^*}^{cong,stage1}$ where c^* is the index number of the iteration that yields the optimal solution, which is the solution to the the first stage loss minimization:

$$Loss_l^{stage1} = \min_{prLMP_{ilc}^{cong}} \left(\sum_i (daLMP_{il}^{cong} - prLMP_{ilc}^{cong})^2 \right)$$

Next, we can calculate the standard deviations across the five PJM regions of the congestion LMP residuals:

$$std_l^{congLMP} = std \left(\sum_i (daLMP_{il}^{cong} - prLMP_{ilc^*}^{cong,stage1}) \right)$$

In the second stage, we re-perform the grid search that we did in stage 1, only this time, the loss function is weighted by the standard deviations across five PJM regions calculated above. The solution to this grid search is the second stage optimal model predicted LMPs, $prLMP_{ilc^*}^{cong,stage2}$.

$$Loss_l^{stage2} = \min_{prLMP_{ilc}^{cong}} \left(\sum_i \frac{(daLMP_{il}^{cong} - prLMP_{ilc}^{cong})^2}{std_l^{congLMP}} \right)$$

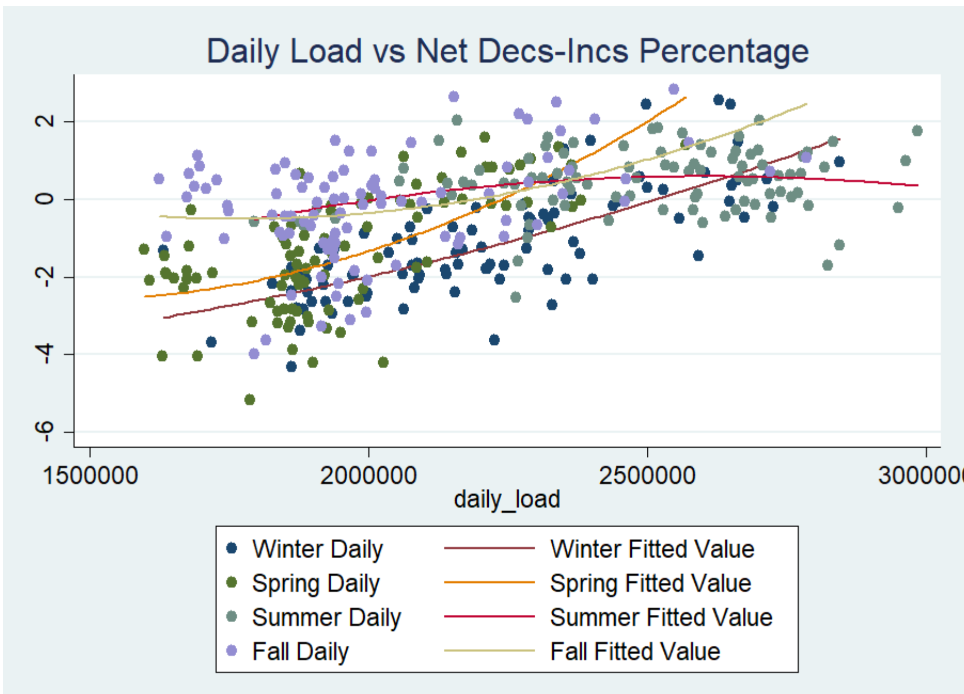
Finally, $\hat{A}_{ilc^*}$ are used as initial values for an optimization search to find the exact scalers ($\hat{A}_{il}$) that minimizes the aggregate gap between the DA congestion LMPs and the model predicted congestion LMPs across the five PJM regions, using the second stage loss function and limiting the lower and upper bounds of these scalers in between the range of $[0.01, 5]$ for all five transmission links. These optimal scalers give us the final optimal model's predicted congestion LMPs, $prLMP_{il}^*$.

3.6 Virtual Bidding

We account for the amount of cleared daily net virtual bid (decs - incs) into our segment loads in our model. We detect a quadratic relationship between daily net virtual bids and daily load in each season. These correlations are shown in the figure below. We use quadratic regression with seasonal fixed effects (W = Winter, S = Spring, Su = Summer, F = Fall) to predict the hourly cleared virtual bid (NVB) and net cleared virtual bid in the load segment level across PJM (L). The daily cleared incs and decs are taken from the dataset "*Daily cleared INCs, DECs, and UTCs*" from *PJM's Data Miner 2: //dataminer2.pjm.com/feed/day_inc_dec_utc/definition (access May 19, 2019).*

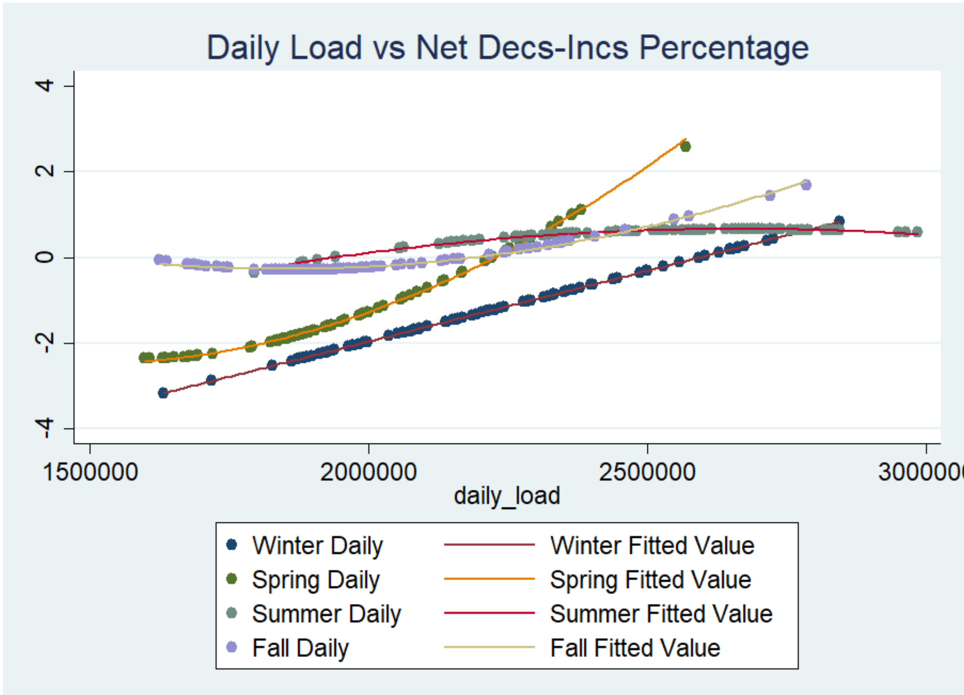
$$\begin{aligned}
\mathrm{NVB}_{daily} &= \beta_1 \left(\mathrm{L}_{daily}\right) + \beta_2 \left(\mathrm{L}^2_{daily}\right) + \delta_1 \left(\mathrm{W}\right) + \delta_2 \left(\mathrm{S}\right) + \delta_3 \left(\mathrm{Su}\right) + \delta_4 \left(\mathrm{F}\right) \\
&+ \sigma_1 \left(\mathrm{W} \times \mathrm{L}_{daily}\right) + \sigma_2 \left(\mathrm{S} \times \mathrm{L}_{daily}\right) + \sigma_3 \left(\mathrm{Su} \times \mathrm{L}_{daily}\right) + \sigma_4 \left(\mathrm{F} \times \mathrm{L}_{daily}\right) \\
&+ \gamma_1 \left(\mathrm{W} \times \mathrm{L}^2_{daily}\right) + \gamma_2 \left(\mathrm{S} \times \mathrm{L}^2_{daily}\right) + \gamma_3 \left(\mathrm{Su} \times \mathrm{L}^2_{daily}\right) + \gamma_4 \left(\mathrm{F} \times \mathrm{L}^2_{daily}\right) + \epsilon
\end{aligned}$$

Figure A.9: Daily Load vs Daily Net Cleared Virtual Bid



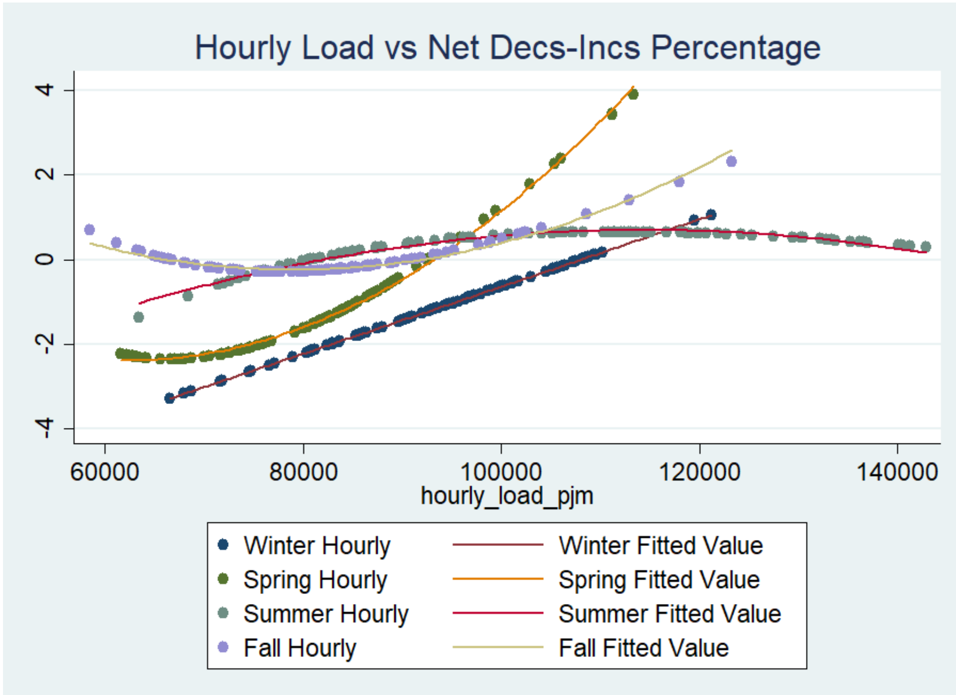
The predicted daily virtual bids from the above regression are shown in the figure below. We can see that the quadratic relationship is a reasonable assumption.

Figure A.10: Daily Load vs Predicted Daily Net Cleared Virtual Bid



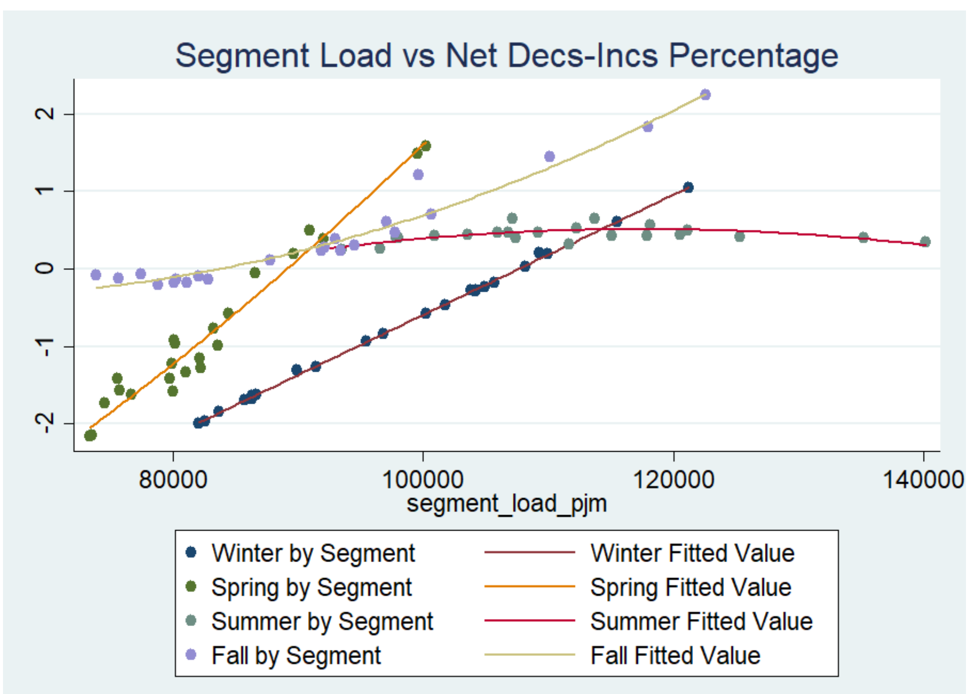
Now, apply the parameters $\beta, \delta, \sigma, \gamma$ found in the regression above (with adjustment to units from daily to hourly) to hourly PJM load, we can predict the net virtual bid cleared every hour across PJM.

Figure A.11: Daily Load vs Predicted Hourly Net Cleared Virtual Bid



Summing all the hours in each load segment, we have a predicted cleared net virtual bid in every load segment as a function of segment load:

Figure A.12: Daily Load vs Predicted Segment Net Cleared Virtual Bid



These predicted net cleared virtual bids by segment are divided by the total PJM load in corresponding load segments to find the percentage of net cleared bid in total load in that segment, denoted as z_l, where $l = 1, 2, 3, ..., 96$. The final segment loads used in the model is defined as:

$$L_{il}^{*} = L_{il}\left(1 + z_l\right)$$

in which, $i = 1, 2, 3, 4, 5$ are the index for 5 regions in our model and $l = 1, 2, ..., 96$ are the index for 96 load segments in our model. L_{il} is the original load in each load segment in each region and L_{il}^{*} is the final load in each load segment in each region after accounting for net virtual bid in that segment.

3.7 List of Calibrated Parameters

Table A.6: List of Calibrated Parameters.

Parameters	Description	Source
Sets		
J	Set of aggregate EGUs	
J_{RGGI}	Set of EGUs in RGGI states in PJM	
I	Set of regions	
S	Set of PJM states	
L	Number of load segment	
t	RPS categories	
δ_l	Number of hours in load segment l	
Supply Side		
ψ_{js}^{E}	Heat rate of existing EGU j	CEMS, SNL, eGrid, NEEDS
ϕ_{js}^{EP}	Emission rate of existing EGU j of pollutant P	
$\bar{g}_{js}^{E}$	Effective capacity of existing EGU j	SNL, NEEDS
γ_{js}^{N}	Effective capacity of new EGU j	SNL, NEEDS
$\bar{R}_j$	Amount of RECs from external EGU j provided to PJM	
m_{jl}^{E}	Supply curve slope for existing EGU j in segment l	
b_{jl}^{E}	Supply curve intercept for existing EGU j in segment l	
b_{jls}^{N}	Total marginal cost of new EGU j in segment l	
K_j^{N}	Capital cost for new EGU j in state s	
Demand Side		
η^n	Demand elasticity	Bushnell et al. (2017).
n_{il}	Demand curve slope in region i and segment l	PJM Data Miner 2.
c_{il}	Demand curve intercept in region i and segment l	PJM Data Miner 2.
ϵ_l	Gross system loss as percentage of load in segment l.	
Transmission		
$\bar{f}_{ihl}$	Transmission capacity in region i and segment l	SNL.
Policies		
m^{NPJM}	CO_2 emission curve slope from non-PJM RGGI states.	
b^{NPJM}	CO_2 emission curve intercept from non-PJM RGGI states.	
m^B	Banked allowance curve slope from PJM and RGGI states.	
b^B	Banked allowance curve intercept from PJM and RGGI states.	
$\bar{B}$	Banked allowance from PJM and RGGI states in previous year	
$\bar{R}_{st}$	RPS target in state s of category q	
$\bar{E}_{RGGI}$	RGGI emission cap.	

4 Emissions Calculations

Source emissions from pollutant $P = \mathrm{CO_2, SO_2, NOx, PM, VOC, NH_3, CO}$ in a given year can be calculated *ex post* from generation from existing and new EGU j according to, respectively:

$$e_j^{E,P} = \phi_j^{E,P} g_{jl}^{E}, \text{ and}$$
$$e_j^{N,P} = \phi_j^{N,P} g_{jl}^{N}, \tag{27}$$

where $\phi_j^{E,P}$ and $\phi_j^{N,P}$ are the emissions intensity of existing and new EGU j from pollutant P.

4.1 Emissions Intensity Calibration

4.1.1 CO_2, SO_2, NOx

To assign CO_2, SO_2, NOx emission rates to each EGU, we also perform a similar procedure as the procedure to assign heat rate in section 3.2.2 above, but for emission rates. This means, first, we assign the CEMS's CO_2 emission rates to the EGUs that are in CEMS in the final dataset (374 units). For the remaining 2,721 EGUs, we use the eGrid's threshold for CO_2 emission rate (eGrid's average emission rate plus two times its standard deviation) to make a cut-off and assign CO_2, SO_2, NOx emission rates for EGUs in eGrid that have CO_2 emission rates below this cut-off (1,519). For the remaining 1,202 EGUs, we finally repeat the same process for SNL dataset, which is setting the SNL's threshold for CO_2 emission rate (SNL's average emission rate plus two times its standard deviation) to make a cut-off and assign CO_2 emission rates for the remaining EGUs in SNL that have CO_2 emission rates below this cut-off. After this step, we are able to assign CO_2 emission rates to all EGUs in our final dataset. However, since the SNL data does not include emission rates for SO_2 and NOx, we are unable to assign SO_2, NOx emission rates to these 1,202 EGUs. Summary of emission rate assignment is shown in Table A.7.

To assign SO_2 and NOx emission rates to these remaining 1,202 EGUs, we use quadratic regression, after assigning SO_2 andNOx emission rates of zero for EGUs that have fuel-types of wind, hydro, solar and nuclear (543). After this, we only need to assign SO_2, NOx emission rates to 659 remaining non-renewable and non-nuclear EGUs. We perform quadratic regressions of SO_2 and NOx emission rates on fuel types, heat rates, and effective capacities as follows:

$$\phi_{\tilde{j}l}^{E,P} = \beta_0 + \mu\left(fuel_{\tilde{j}}\right) + \beta_1\left(\psi_{\tilde{j}}^{E}\right) + \beta_2\left(\psi_{\tilde{j}}^{E}\right)^2 + \beta_3(K_{\tilde{j}l}^{E}) + \beta_4\left(K_{\tilde{j}l}^{E}\right)^2 + \mu_{\tilde{j}l}, \tag{28}$$

R^2 for the regressions for SO_2 emission rates and NOx emission rates of these EGUs are 0.62 and 0.60 respectively.

CO_2, SO_2 and NOx emission rates of new NGCC EGUs are the average of CO_2, SO_2 and NOx emission rates of existing NGCC EGUs.

Table A.7: Emission Rate Assignments to Units in Final Dataset.

Dataset/Method	EGUs Assigned CO_2 Emission Rates	EGUs Assigned SO_2 and NOx Emission Rates
Final Dataset	3,095	3,095
CEMS	374	374
eGrid	1,519	1,519
SNL	1,202	–
Regression	–	1,202

4.1.2 PM, NH_3, VOC, CO

To impute emission rates for PM (PM_{25} and PM_{10}), NH_3, VOC, and CO, we follow the instruction for calculation emissions that is detailed in the EPA's *flat file generation methodology v514* (accessed 05/19/2020) with slight modifications regarding assignments of sulfur and ash contents.

We first use generation weighted sulfur content and ash contents by state and PJM region from the *EPA 5-13_Base_Case RPE Replacement File* from the IPM v514 base case output first, then we link the heat contents with these sulfur and ash contents from *Table 9-5, page 276 (9-13), Documentation for EPA Base Case v.5.13 Using the Integrated Planning Model.* After that we use the *PMAshSulfurContent* tab in the *flatfile_inputs_1* to assign sulfur and ash contents for the EGUs that are still not assigned ones from the previous step. Finally, we use *Table 12, flat file generation methodology v514* to assign sulfur and ash contents for the remaining EGUs.

Ater assigning sulfur and ash contents for the all the EGUs in our final dataset, we follow the *flat file generation methodology v514* using the sulfur and ash contents we establish to calculate PM (PM25 and PM_{10}), NH_3, VOC, and CO emission rates for all the EGUs. Note that while the *flat file generation methodology v514* instructs us to calculate total annual emissions from these pollutants, we only calculate emission rates for these pollutants by using heat rates instead of heat inputs in all of the formulas in *flat file generation methodology v514*.

To validate the above methodology of imputing emission rates, we use three data files: the NEEDS, the *Web-Ready_Parsed_File_EPA5-13_Base_Case_2018* file and the *FlatFile_EPA513_BC_7c_2018_20131108* file. We first merge the NEEDS dataset with the *Web-Ready_Parsed_File_EPA5-13_Base_Case_2018* to link total annual generation to each EGU in the NEEDS. Using the methodology of calculating emission rates established above, we take our calculated emission rates times the total annual generation to get the total annual emissions for all the EGUs in the NEEDS. Finally, we merge the combined data to the *FlatFile_EPA513_BC_7c_2018_20131108* which has total annual emissions by pollutants calculated by the EPA. We use these annual emissions calculated by the EPA to validate our calculated annual total emissions.

Our imputed EGU-level total annual emissions match well with the annual emissions calculated by the EPA. For pollutants NH_3, VOC, CO, our imputed emissions are matched almost exactly with EPA's calculated emissions with R^2 of 0.99. For PM_{25}, and PM_{10}, our imputed emissions from natural gas EGUs are matched almost exactly with EPA's calculated emissions, with $R^2 = 1$. For all fuel types, our imputed emissions are also matched well with EPA's calculated ones, with $R^2 > 0.91$ consistently.

4.2 Estimation of CO_2 Abatement by RGGI states Not in PJM and RGGI Allowance Bank

The model developed by Landry and Pham (2020) was designed to reflect the scale in which electricity dispatch and new capacity expansion decisions are actually made within the wholesale electricity market operated by PJM. RGGI of course encompasses states located within two other significantly sized wholesale electricity markets: the wholesale electricity market that includes Maine, Vermont, New Hampshire, Massachusetts, Connecticut, and Rhode Island which is managed by the New England Independent System Operator (ISONE), and the wholesale electricity market encompassing New York operated by the New York Independent System Operator (NYISO). It was not feasible to expand the model developed by Landry and Pham (2020) to encompass the market decisions made in each of these two markets. Moreover, such a model would require us to make strong assumptions regarding how power flows economically between these two regional wholesale electricity markets and PJM.

Since our focus is on understanding Pennsylvania's entry into RGGI and Pennsylvania is a critical member of PJM, all that is really necessary is for us to proceed is to account for CO_2 emissions from RGGI states not in PJM and changes in allowances that have been banked by RGGI market participants historically (in PJM or otherwise). Given the rich data available to us from RGGI, we are able to do so quite credibly reflecting the revealed economic decisions made by RGGI market participants since RGGI's first allowance market that opened in 2009. We treat these economic decisions in a reduced form manner, meaning we do not explicitly characterize how changes in electricity dispatch in PJM affects auction prices–for which we do not have data–but instead identify the RGGI market equilibrium using plausibly exogenous instrumental variables. We then use these two reduced form equations to extend the model developed by Landry and Pham (2020) to allow us to characterize market clearing in the RGGI cap and trade system.

To this end, we use three stage least squares (3SLS) to simultaneously estimate the following system of equations using quarterly data from 2009 to 2019:

$$B_t = \beta_0 + \beta_1 P_t + \beta_2 B_{t-1} + \beta_3 D_{NJinRGGI,t} + \beta_4 D_{q2,t} + \beta_5 D_{q3,t} + \beta_6 D_{q4,t} + \epsilon_t, \tag{29}$$

$$E_t = \gamma_0 + \gamma_1 P_t + \gamma_2 D_{CP2,t} + \gamma_3 D_{CP3,t} + \gamma_4 D_{q2,t} + \gamma_5 D_{q3,t} + \gamma_6 D_{q4,t} + \gamma_7 R_t + \gamma_8 D_{CP4,t} + \nu_t,$$

$$P_t = \delta_0 + \delta_1 Q_t + \delta_2 D_{CPA1,t} + \delta_3 D_{CPA2,t} + \delta_4 D_{q2,t} + \delta_5 D_{q3,t} + \delta_6 D_{q4,t} + \delta_7 R_t + \varepsilon_t.$$

where: B_t is the amount of banked permits as of t, B_{t-1} is the amount of banked permits as of $t-1$, P_t is the market clearing price of permits at auction, $D_{NJinRGGI,t}$ is a dummy equal to one if New Jersey is in RGGI in t and zero otherwise, $D_{q2,t}$ is a dummy equal to one if t corresponds to quarter two, $D_{q3,t}$ is a dummy equal to one if t corresponds to quarter three, $D_{q4,t}$ is a dummy equal to one if t corresponds to quarter four, Q_t is the quantity of permits offered at auction in t, $D_{CPA1,t}$ is a dummy that equals one if the first control period adjustment is in effect, $D_{CPA2,t}$ is a dummy that equals one if the second control period adjustment is in effect, R_t is the quarterly average of the daily bank discount rate for treasury bills with four week maturation, E_t is total CO_2 emissions from covered EGUs in RGGI states that are not in PJM, $D_{CP2,t}$ is a dummy equal to one if t is in control period two, $D_{CP3,t}$ is a dummy equal to one if t is in control period three, and $D_{CP4,t}$ is a dummy equal to one if t is in control period four.

R_t is calculated from the daily bank discount rates for treasury bills with four week maturation as reported in the U.S. Department of the Treasury's *Daily Treasury Bill Rates Data*.

E_t is calculated from quarterly level data on CO_2 emissions from covered EGUs in RGGI from RGGI's CO_2 Allowance Tracking System (COATS) for the subset of units in RGGI states that are not in PJM. We assume that if a unit is "not operating" that it releases zero CO_2 emissions.

The amount of permits added to the permit bank in a quarter are assumed to equal the number of permits sold in the quarterly RGGI auction as reported in RGGI's *Allowance Prices and Volumes* dataset plus the amount of permits not-auctioned in the quarter less the CO_2 emissions from covered EGUs in all RGGI states aggregated from EGU level quarterly emissions from COATS. B_t is the cumulative sum of these additions and subtractions to the bank (restricted to be non-negative) as of quarter t and B_{t-1} is the one quarter lag of B_t.

The amount of permits not-auctioned in the quarter equals the quantity of permits offered at auction in the quarter multiplied by the share of non-auctioned permits in the associated year to the total amount of permits offered in the associated year.[4] The quantity of permits offered at auction in the quarter is taken from RGGI's *Allowance Prices and Volumes* dataset. The total

[4]Permits sold in 2008 before the beginning of the first control period in 2009 are added to the permits offered in 2009.

amount of permits offered in a year is calculated from the quarterly amount of permits offered. The amount of non-auctioned permits by year equals the CO_2 Allowance Adjusted Budget plus the amount of permits released by the Cost Containment Reserve (CCR) less the quantity of permits offered at auction that year. The CO_2 Allowance Adjusted Budget and the amount of permits released by the CCR are taken from RGGI's Distribution of 2009-2020 Allocation Year CO_2 Allowances datasets. The quarterly allowance price at auction, P_t is also taken from RGGI's *Allowance Prices and Volumes* dataset.

All remaining dummy variables are defined based upon the years associated with each of the four control periods and the years in which the CO_2 Allowance Budget was modified by the first and second control period adjustments.

The first equation in (29) is a reduced form representation of the first-order condition of an economic agent's inter-temporal profit maximization decision to bank permits. The second equation is a reduced form representation of a representative generator's (here, reflecting generation across all non-PJM RGGI states) profit maximizing decision to reduce CO_2 emissions for compliance with RGGI. Concurrently, this also reflects the representative generator's demand for permits at auction. The third equation reflects market clearing in the RGGI primary allowance auction, where Q_t reflects the supply of new permits offered at auction.

Taken together the last two equations in (29) reflect the conventional structural estimation of the supply and demand of permits. Given the exogenous variables in these equations, these two equations identify the endogenous market clearing price for permits sold at auction, which, together with additional exogenous variables, is used to estimate the decision to withdraw (demand) or add (supply) permits in t to the bank. We use quarterly level data for which we have a complete series from quarter 1 of 2009 to quarter 4 of 2019.

Given the estimated parameters from (29) which are estimated using quarterly data, we construct the supply/demand of banked permits on an annual basis using the first equation and the supply of non-PJM RGGI abatement on an annual basis using the second equation. The supply/demand for banked permits is adjusted across years in light of the amount of permits in the bank account in the previous year given the estimated β_2. The net economic benefit to RGGI states that are not in PJM from reduced CO_2 abatement costs, $TAB_y\left(E_y^{NPJM}\right)$ and the net economic benefit to banked allowance holders from the change in the inter-temporal value of banked permits, $TBB_y\left(B_y; B_{y-1}\right)$ are calculated by integrating under these annual marginal curves and treating B_{y-1} as exogenous. These two components of economic welfare are then included in the objective function of the numerical model. The RGGI allowance market thus clears annually when:

$$E_y^{PJM} + E_y^{NPJM} \leq \bar{E} - \left(B_y - B_{y-1}\right), \tag{30}$$

where E_y^{PJM} is total CO_2 emissions from EGUs in PJM that are covered under RGGI in year y, E_y^{NPJM} is total CO_2 emissions from covered EGUs in RGGI states that are not in PJM in year y, $\bar{E}$ is the RGGI CO_2 emissions cap in year y, B_y is the amount of permits in the bank in year y, and B_{y-1} is the exogenous amount of permits in the bank as of the previous year $y-1$. Given that the shadow price on (30) is the market clearing allowance price in the solution obtained by the numerical model, the inclusion of $TAB_y\left(E_y^{NPJM}\right)$ and $TBB_y\left(B_y; B_{y-1}\right)$ in the model's objective function implies that when the numerical model is solved the first-order conditions with respect to E_y^{NPJM} and B_y reflect the respective annual marginal equations.

5 Intertemporal Dynamics

5.1 Load Growth

Annual load growth rate for future load projection in the model is 0.42% increase from the previous year, which is the result of a linear forecast based on the actual loads of the past five years in PJM as reported by Market Monitoring Analytics in their State of the Market Reports 2013-2018.

5.2 Fuel Prices

Fuel prices are grown from the 2018 fuel price baseline. We use data for fuel price growth rates from the 2018 Annual Energy Outlook (AEO 2018) for the Mid-Atlantic region published by the U.S. Energy Information Administration (EIA). We apply price growth rates for natural gas, coal, oil and uranium and assume that prices for other fuel types stay the same as in 2018. Compared to the 2018 baseline, the fuel price growth rates from 2019-2030 used in our model are as follows:

Table A.8: Fuel Price Growth Rates 2019 - 2030 compared to 2018 (in $\%$).

	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Natural Gas	9.03	14.71	11.94	12.18	14.69	16.38	18.89	18.98	19.77	19.36	21.82	21.63
Coal	0.84	1.92	2.07	2.02	2.00	2.42	2.82	2.86	2.63	2.66	3.18	3.40
Distillate Oil	8.98	33.91	46.75	53.93	59.90	61.07	61.73	61.88	63.76	65.23	67.84	69.27
Uranium	0.15	0.46	0.62	0.77	1.08	1.23	1.54	1.69	2.00	2.16	2.31	2.62

5.3 External RECs

Observing the total number of RECs that are eligible to be supplied to PA and RPJM states in 2016 and 2017, we assume an annual growth rate of 4% in number of RECs that are allowed to be imported into PA and an annual growth rate of 5% in number of RECs that are allowed to be imported into RPJM states.

5.4 Capital Costs

For new NGCC EGU's capital cost, we assume no growth rate, which means capital cost for new NGCC EGUs is still kept at $\$73,900$ MW-year. For new wind EGU's capital cost, Wiser et al (2016) surveys different wind technology experts and finds that onshore wind costs would decline by 24% by 2030 relative to 2014, which is translated to an annual average reduction rate of 1.7%. For new solar PV system's capital cost, we look at the EIA's Sunshot Initiative which has targeted a 50%reduction in utility scale solar PV costs from their 2020 target, which was achieved in 2017, to their 2030 target. We think this may be too ambitious so we cut it in half and assume a 25% reduction in PV costs by 2030 relative to 2017. This implies an annual average PV reduction rate in PV costs of 2.19%.

6 Additional Details on Pre-existing Policies

6.1 The Acid Rain Program

The Acid Rain Program (ARP) was established under Title IV of the Clean Air Act (CAA) Amendments, which established $\mathrm{SO_2}$ and NOx emission allowance trading program for $\mathrm{SO_2}$ and NOx emitting EGUs. To model this, we add onto the total marginal costs of the $\mathrm{SO_2}$ and NOx emitting EGUs in our final dataset the regulatory costs of buying $\mathrm{SO_2}$ and NOx emission allowance to comply with the ARP. These pre-existing regulatory costs are discussed in section 3.2.2, particularly in equation (20).

6.2 Nuclear Subsidies

In the states of Illinois and New Jersey, eligible nuclear EGUs are eligible for the Zero Emission Certificates (ZECs).

6.2.1 Nuclear Subsidies in New Jersey

In New Jersey, the nuclear subsidy program started in 2019. The program established a ZEC price and eligible nuclear EGUs in New Jersey can receive an amount of subsidy equivalent to this ZEC price for every MWh of generation they produce.

To calculate the ZEC price in New Jersey, we follow the ZEC calculation method mentioned in New Jersey's ZEC Act Legislation, taken from chapter 16 of the legislation: //www.njleg.state.nj.us/2018/Bills/AL18/16_.HTM (accessed 02/12/2020). To calculate ZEC price in New Jersey, we divide the full recovery of all costs associated with the electric public utility's required procurement of ZECs at the end of the prior energy year by the greater of: 40% of the total number of MWhs of electricity distributed by the electric public utilities in the State in the prior energy year, or the number of MWhs of electricity generated in the prior energy year by the selected nuclear power plants. New Jersey approved to subsidize 3 nuclear EGUs so far, which are Hope Creek, and Salem 1 and 2, which total 28,441,726 MWh which is less than 40% of total New Jersey's generation which is $0.4 * 74,908,250 = 29,963,300$ MWh.

In simpler terms, the formula for calculation of ZEC price is New Jersey is given by:

$$\frac{min\{p^{RP}g^{RS}; 3,000,000\}}{29,963,300}$$

where p^{RP} is electricity price charged to rate payers in $/MWh in and g^{RS} is the total electricity sold to consumer in MWh. In 2019, $p^{RP} = \$4$ and $g^{RS} = 76,016,762$ MWh. Therefore, the total electricity retail sale in 2019 in New Jersey is $\$4 * 76,016,762 = \$304,067,048$, which exceeds the $\$3,000,000$ threshold. Therefore, the ZEC price in New Jersey in 2019 is $\frac{\$3,000,000}{29,963,300}$ = $10.012.

To model this, we subtract $10.012 from the total marginal costs of these nuclear EGUs in New Jersey for every MWh they produce.

6.2.2 Nuclear Subsidies in Illinois

In Illinois, ZEC price is $16.5 unless the subtraction of the average of the Social Cost of Carbon (SCC) and the difference between the average of the market price indices and the baseline market price index is less than zero. In that case, ZEC price is zero.

The average of the SCC is $16.5/MWh, the average of the market price indices taken from my model for year 2019 is $35.35 and the baseline market price index is $31.40 as defined in subparagraph (B) of paragraph (1) of subsection (d-5) of the Illinois Power Agency Act: Section 1-75(d-5), known as the Zero Emission Standard. Since $16.5 - (35.35 - 31.40) = 12.55 > 0$, ZEC price in Illinois is $16.5.

To model this, we subtract $16.5 from the total marginal costs of the nuclear EGUs in Illinois for every MWh they produce.

6.3 Regional Greenhouse Gas Initiative (RGGI)

The Regional Greenhouse Gas Initiative (or RGGI) is the regional emission cap-and-trade program in the Northeast to limit carbon pollution from fossil-fuel EGUs with capacity of 25 MW or more. Currently there are ten states participating in RGGI: Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, and Vermont.

New Jersey left the program in 2011 but re-entered the program in January 2020. Virginia passed the Clean Economy Act in both the House and Senate recently and is set to join RGGI in 2021. Pennsylvania also received executive order in October 2019 to commit the state to joining RGGI in 2022.

The RGGI program sets a cap on the amount of carbon pollution that effected EGUs in the participating states are allowed to emit each year. This cap is declining over the years. Affected EGUs must purchase allowances for the CO_2 emission they emit. These allowance purchases generate revenues for participating states to invest in energy efficiency, clean energy, and other state-level programs. The control periods are every three years. There are currently four control periods: 2009-2011, 2012-2014, 2015-2017, and 2018-2020.

Every quarter, the participating states issue a number of allowances equal to their cap, which declines over the years as the cap declines. After every three years, each EGU must report its total carbon emissions and submit an equal number of emission allowances that cover these emissions. Starting in the third control period (2015), each EGU must hold a number of allowances equal to 50% of its CO_2 emissions during the first two calendar years of each three-year control period. Each EGU then must hold the number of allowances equal to 100% of its remaining emissions for the three-year control period at the end of the three year control period.

6.4 Renewable Portfolio Standards (RPS)

Many states in PJM have legislation on a defined percentage of supplied generation be served by renewable resources, for which definitions vary by state. These are called renewable portfolio standards (RPS). In 2018, there are 9 states that have RPS. They are Delaware, Illinois, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, and Washington, DC. There are two states that have voluntary RPS (Virginia and Indiana) and two states that do not have RPS (Kentucky, Tennessee and West Virginia). We only model RPS in the 9 states that have required RPS, of which 4 states (DC, MD, NJ and PA) classify their RPS into tier 1 and tier 2 RPS, under which different eligible renewable energy technologies are clearly defined in each state. The other

5 states (DE, IL, MI, NC and OH) do not classify their RPS into different tiers in 2017 but their eligible technologies are for the most part identical to tier 1 resources and will be modeled as tier 1 resource. By 2030, DC's tier 2 RPS will go down to 0 % and thus in 2030 only tier 1 RPS is modeled for DC. Details on RPS percentages and eligible technologies by tier in each state are shown in table below.

Table A.9: List of RPS regulations by State in PJM in 2017.

PJM State	State Number	RPS Tier 1	RPS Tier 2	Solar RPS
DC	1	13%	1.5%	0.98%
DE	2	16%	N/A	1.5%
IL	3	11.5%	N/A	6%
IN	4	N/A	N/A	N/A
KY	5	N/A	N/A	N/A
MD	6	13.1%	2.5%	1.15%
MI	7	10%	N/A	N/A
NC	8	6%	N/A	0.14%
NJ	9	13.5%	2.5%	3%
OH	10	3.5%	N/A	0.22%
PA	11	6%	8.2%	0.2933%
TN	12	N/A	N/A	N/A
VA	13	N/A	N/A	N/A
WV	14	N/A	N/A	N/A

Table A.10: List of RPS regulations by State in PJM in 2030.

PJM State	State Number	RPS Tier 1	RPS Tier 2	Solar RPS
DC	1	42%	0%	4.5%
DE	2	25%	N/A	3.5%
IL	3	25%	N/A	6%
IN	4	10%	N/A	N/A
KY	5	N/A	N/A	N/A
MD	6	20%	2.5%	2.5%
MI	7	35%	N/A	N/A
NC	8	12.5%	N/A	0.2%
NJ	9	50%	2.5%	2.21%
OH	10	12.5%	N/A	0.5%
PA	11	8%	10%	0.5%
TN	12	N/A	N/A	N/A
VA	13	N/A	N/A	N/A
WV	14	N/A	N/A	N/A

Table A.11: List of state-level RPS eligible technologies by tier.

State	Tier 1 RPS	Tier 2 RPS	Eligible Location
DC	(1) Solar PV, (2) solar thermal, (3) wind, (4) biomass (¿65% efficiency),(5) methane from a landfill or wastewater treatment plant, (6) geothermal, (7) ocean including energy from waves, tides, currents, and thermal differences, (8) fuel cells that produces electricity from a Tier 1 renewable source.	(1) Hydroelectric power other than pump storage generation. The facility must have existed and been operational as of January 1, 2004	Sources must be located (1) within the PJM region or (2) an adjacent state to the PJM region or (3) outside the PJM region or adjacent state but in a control area that is adjacent to the PJM Region, if the electricity is delivered into the PJM Region.
DE	(1) Solar, (2) wind, (3) ocean, (4) geothermal, (5) fuel cell powered by renewable fuels, (6) combustion of gas from the anaerobic digestion of organic material, (7) small hydroelectric facility ($\leq$ 30 MW), (8) sustainable biomass excluding waste to energy, (9) landfill methane gas	(1) Units in commercial operation after 12/31/1997. No more than 1 percent of each year's sales may come from resources that are not new	Sources must be located (1) within or (2) imported into the PJM region.
IL	(1) Wind, (2) solar thermal energy, (3) PV cells and panels, (4) bio-diesel, (5) anaerobic digestion, (6) crops and untreated and unadulterated organic waste biomass, (7) tree waste, in-state landfill gas, (8) hydro-power that does not involve new construction or significant expansion of hydro-power dams, (9) other alternative sources of environmentally preferable energy.		Sources must be located (1) in IL or (2) from adjoining states if approved by the Illinois Power Agency, or (3) within portions of the PJM and MISO footprint in the US.

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Table A.11 – *Continued from previous page*

State	Tier 1 RPS	Tier 2 RPS	Eligible Location
IN* 4	(1) Solar energy, (2) PV cells and panels, (3) dedicated crops grown for energy production, (4) organic waste biomass, (5) hydro-power, (6) fuel cells, (7) hydrogen, (8) energy from waste to energy facilities including energy derived from advanced solid waste conversion technologies, (9) energy storage systems or technologies, (10) geothermal energy, (11) coal bed methane, (12) industrial byproduct technologies that use fuel or energy that is a byproduct of an industrial process, (13) waste heat recovery from capturing and reusing the waste heat in industrial processes for heating or for generating mechanical or electrical work, (14) landfill methane recovery, (15) demand side management or energy efficiency initiatives, (16) a clean energy project described in the statute, (17) nuclear energy, (18) distributed generation connected to the grid, (19) combined heat and power, (20) electricity that is generated from natural gas at a facility constructed in Indiana after July 1, 2011 which displaces electricity generation from an existing coal fired generation facility.		At least 50 percent of RECs must be purchased from resources located within Indiana.
KY	No RPS.		

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Table A.11 – *Continued from previous page*

State	Tier 1 RPS	Tier 2 RPS	Eligible Location
MD	(1) Solar, (2) wind, (3) qualifying biomass, (4) methane from a landfill or wastewater treatment plant, (5) geothermal, (6) ocean, (7) fuel cell powered by methane or biomass, (8) small hydroelectric plant (¡ 30 MW), (9) poultry litter incineration facilities in Maryland, (10) waste-to-Energy facilities in Maryland, (11) certain geothermal heating and cooling systems and biomass systems that generate thermal energy.	(1) Hydroelectric power other than pumped storage generation	Source must be (1) located in the PJM Region; or (2) outside the area described in item (1) but in a control area that is adjacent to the PJM service territory, if the electricity is delivered into the PJM service territory. Solar resources must be connected to the distribution grid serving Maryland.
MI	(1) Biomass, (2) solar PV, (3) solar thermal, (4) wind, (5) geothermal, (6) municipal solid waste (MSW), (7) landfill gas, (8) existing hydroelectric, (9) tidal, wave, and water current (e.g., run of river hydroelectric) resources.		Resources must be located within Michigan or anywhere in the service territory of retail electric provider in Michigan that is not an alternative electric supplier. There are many exceptions to these requirements.

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Table A.11 – *Continued from previous page*

State	Tier 1 RPS	Tier 2 RPS	Eligible Location
NC	(1) Solar-electric, (2) solar thermal, (3) wind, (4) hydro-power ($\leq$ 10 MW), (5) ocean current or wave energy, (6) biomass that uses Best Available Control Technology (BACT) for air emissions, (7) landfill gas, (8) combined heat and power (CHP) using waste heat from renewables, (9) hydrogen derived from renewables, (10) and electricity demand reduction. Up to 25% of the requirement may be met through energy efficiency technologies, including CHP systems powered by non-renewable fuels. After 2021, up to 40% of the standard may be met through energy efficiency.		Dominion, the only utility located in both the state of North Carolina and PJM, may purchase RECs from anywhere.
NJ	(1) Solar technologies, (2) PV technologies, (3) wind energy, (4) fuel cells powered by renewable fuels, (4) geothermal technologies, (5) wave or tidal action, (6) methane gas from landfills or a biomass facility provided that the biomass is cultivated and harvested in a sustainable manner, (7) hydroelectric facilities ($\leq$ 3 MW) that are located in NJ and placed in service after July 23, 2012.	(1) Resource recovery facility (subject to qualifications), (2) small hydroelectric power facility (¡ 30 MW)	Source must be (1) within or (2) delivered into the PJM region. If the latter, the energy must have been generated at a facility that commenced construction on or after January 1, 2003

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Table A.11 – *Continued from previous page*

State	Tier 1 RPS	Tier 2 RPS	Eligible Location
OH	(1) Solar photovoltaics (PV), (2) solar thermal technologies used to produce electricity, (3) wind, (4) geothermal, (5) biomass, (6) biologically derived methane gas, landfill gas, certain non-treated waste biomass products, (7) solid waste (as long as the process to convert it to electricity does not include combustion), (8) fuel cells that generate electricity, certain storage facilities, and qualified hydroelectric facilities, (9) certain co-generation and waste heat recovery system technologies that meet specific requirements, (10) distributed generation systems used by customers to generate electricity using the aforementioned eligible renewable resources, (11) run-of-the-river hydroelectric systems on the Ohio River (> 40 MW).		Source must be (1) in-state facilities or (2) can be shown to be deliverable into the state.
PA	(1) Solar PV and solar thermal energy, (2) wind power, (3) Low-impact hydro-power, (4) geothermal energy, (5) biologically derived methane gas, (6) generation of electricity utilizing by-products of the pulping process and wood manufacturing process including bark, wood chips, sawdust and lignin in spent pulping liquors (in-state resources only), (7) biomass energy, (8) coal mine methane.	(1) Waste coal, (2) distributed generation systems, (3) demand-side management, (4) large-scale hydro-power (including pumped storage), (5) municipal solid waste, (6) generation of electricity utilizing by-products of the pulping process and wood manufacturing process including bark, wood chips, sawdust and lignin in spent pulping liquors, (7) integrated combined coal gasification technology.	Source must be (1) located inside the geographical boundaries of this Commonwealth or (2) within the service territory of any regional transmission organization that manages the transmission system in any part of this Commonwealth.
TN	No RPS		

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Table A.11 – *Continued from previous page*

State	Tier 1 RPS	Tier 2 RPS	Eligible Location
VA*	(1) Solar, (2) wind power, (3) geothermal energy, (4) hydropower, (5) wave, (6) tidal, (7) biomass energy.		Electricity must be generated or purchased in (1) Virginia or (2) in the PJM service territory.
WV	No RPS		

End of long table.

Notes: * States with voluntary RPS

7 Model Calibration Results

This section reports calibration results in 2016 and 2017 across multiple dimensions: load, generation mix, LMPs, REC prices, predicted new capacities (2017 only), CO_2 emissions.

7.1 2016 Calibration Results

7.1.1 Generation Mix

Table A.12: Calibration Results for Total Generation in PA and RPJM in 2016 (GWh).

Fuel	PA-Actual	PA-Calibrated	PA-Error	RPJM-Actual	RPJM-Calibrated	RPJM-Error
Coal	54,672	54,310	0.66%	220,609	219,465	0.52%
Nuclear	82,924	82,924	0.00%	196,622	196,662	0.00%
Gas	68,048	68,321	-0.40%	146,974	146,104	0.60%
Hydro	2,374	2,375	0.00%	11,312	11,312	0.00%
Wind	3,476	3,476	0.00 %	14,240	14,240	0.00%
Oil	363	355	2.51 %	1,800	1,780	1.15 %
Solar	75	75	0.00%	945	944	0.03%
Biomass	1,883	1,857	1.40%	4,017	4,035	-0.46%
Other	1,250	699	44.00%	958	1,311	-36.85%
Total	215,067	213,392	0.31%	597,478	595,813	0.28%

7.1.2 CO_2 Emissions

Total PJM's CO_2 emission for 2016 is taken from the Monitoring Analytics' 2016 State of the Market, which reports total CO_2 emission of 358.6 MMT. Using CO_2 emission data from 2016 EIA's State Electricity Profiles for Pennsylvania of 89.6 MMT, we can impute rest of PJM's 2016 CO_2 emission of 269.1 MMT. Our model predicts CO_2 emission 87.7 MMT in Pennsylvania, yielding an error of -2.1%. Our model's prediction of Rest of PJM's CO_2 emission is 271.9 MMT in rest of PJM, yielding an error of 1.1%. For the entire PJM, our model predicts total CO_2 emission of 359.6 MMT, which yields a 0.28% error. We slightly under-predict CO_2 emissions in Pennsylvania and slightly over-predict CO_2 emission in rest of PJM.

7.1.3 REC Prices

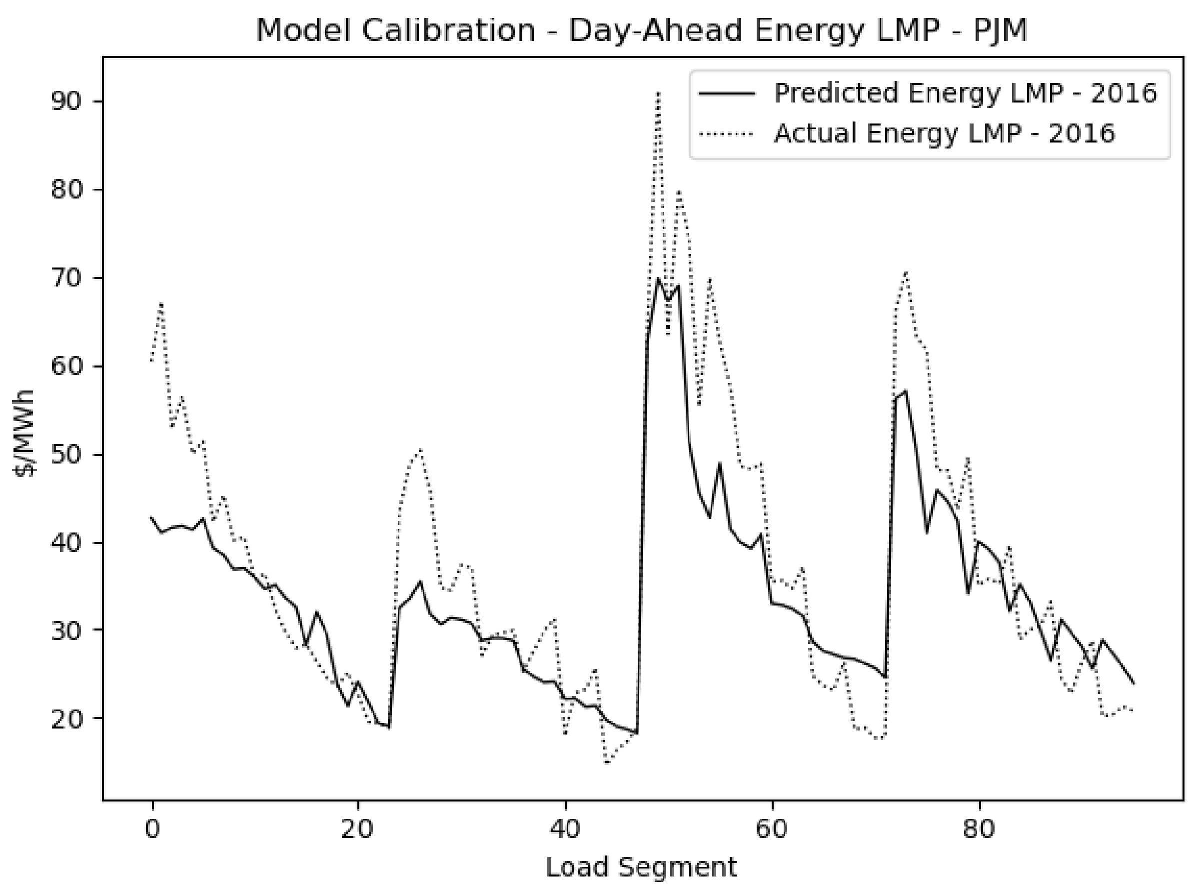
Table A.13: Calibration Results for Generation Weighted REC prices in Pennsylvania and Rest of PJM in 2016.

	PA-Actual	PA-Model	RPJM-Actual	RPJM-Model
Tier 1 Price	\$4.35	\$4.60	\$46.00	\$36.39
Tier 2 Price	\$12.45	\$13.17	\$3.99	\$3.18
SREC Price	\$0.0028	\$0.0029	\$0.48	\$0.38

7.1.4 LMP

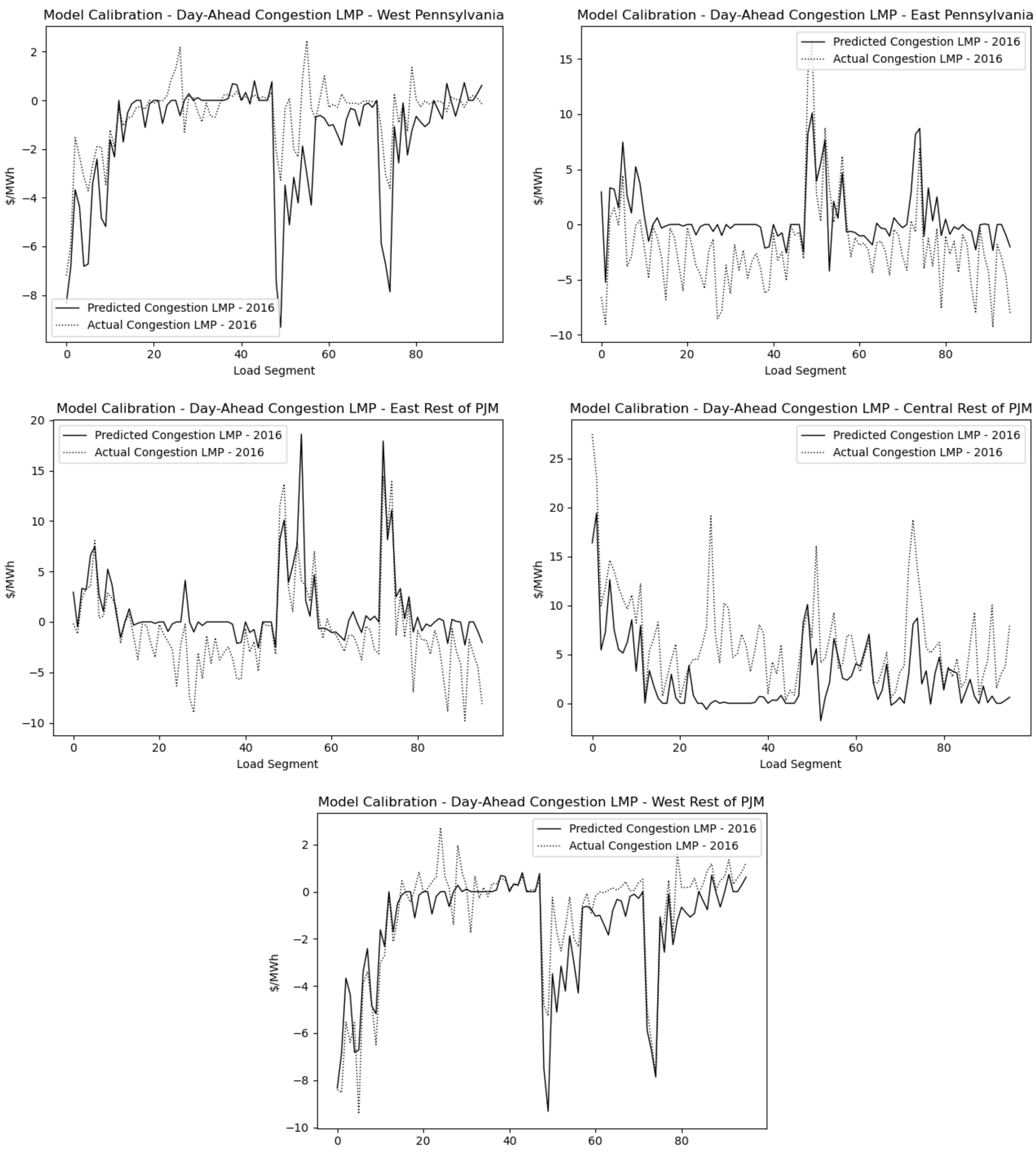
Energy LMP When no transmission constraint is imposed, LMPs are equalized across all regions and are equal to energy LMP. RPAM's prediction of Energy LMP in 2016 has $R^2 = 0.72$, as shown in Figure A.13 below.

Figure A.13: Calibration Results for Day-Ahead Energy LMP for PJM in 2016.



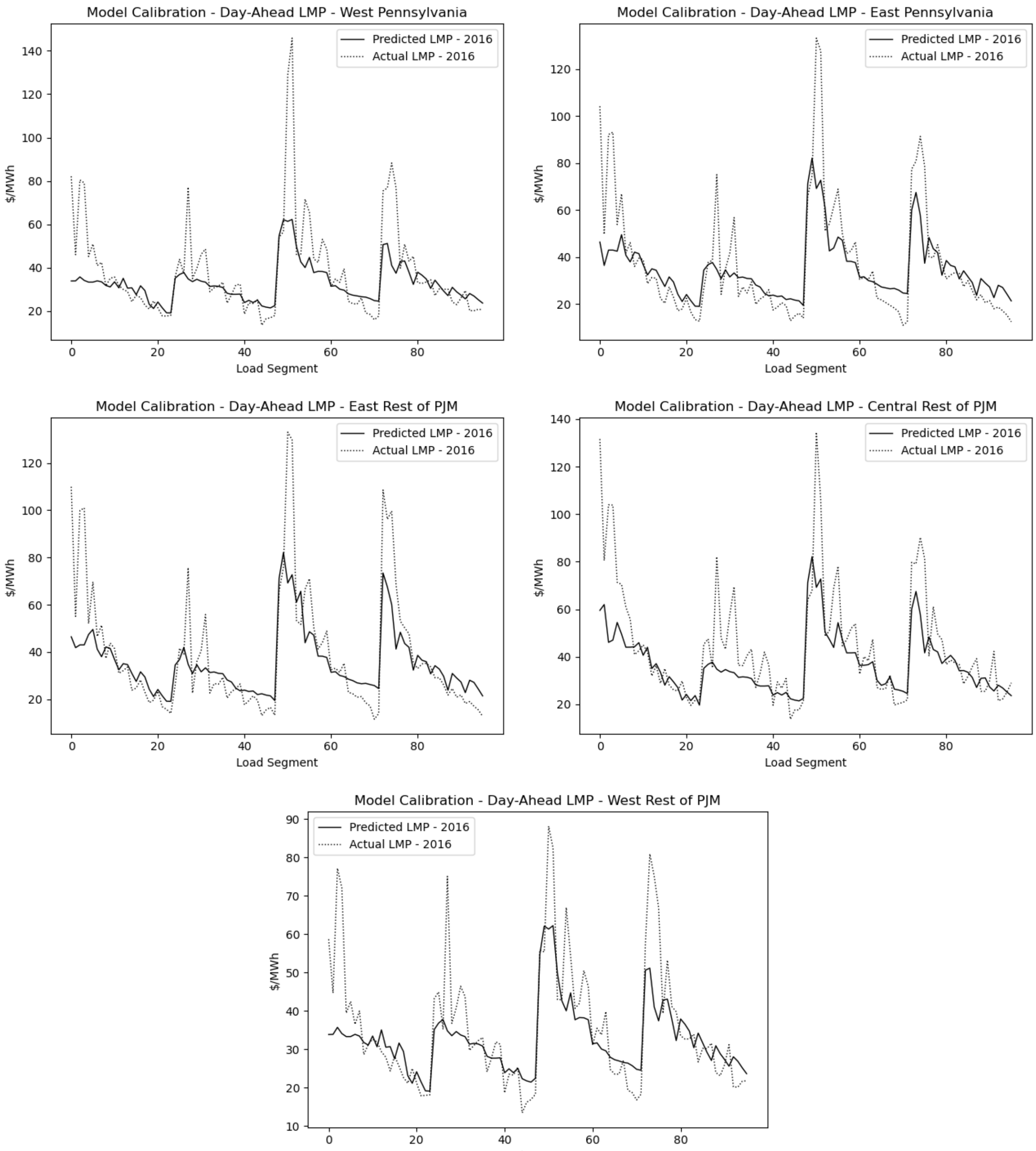
Congestion LMP When transmission constraint in imposed, LMPs are not equalized across regions. Congestion LMPs occur, reflecting the limit in transmission capacities between regions. Our model's predictions of congestion DA LMPs by region in 2016 are shown below.

Figure A.14: Calibration Results for Day-Ahead Congestion LMP in West Pennsylvania (Top Row, Left), East Pennsylvania (Top Row, Right), East RPJM (Second Row, Left), Central RPJM (Second Row, Right) and West RPJM (Bottom Row) in 2016. $R^2 = 0.13$



Total LMP Our model's predictions of total DA LMPs by regions in 2016 are as follows.

Figure A.15: Calibration Results for Day-Ahead LMP in West Pennsylvania (Top Row, Left), East Pennsylvania (Top Row, Right), East RPJM (Second Row, Left), Central RPJM (Second Row, Right) and West RPJM (Bottom Row) in 2016. $R^2 = 0.70$



7.2 2017 Calibration Results

7.2.1 Generation Mix

We compare the generation mix from our model using data on actual generation by fuel type reported by the Monitoring Analytics in their 2017 State of the Market report. The calibration results are shown in the table below.

Table A.14: Calibration Results for Total Generation in PA and RPJM in 2017 (GWh).

Fuel	PA-Actual	PA-Calibrated	PA-Error	RPJM-Actual	RPJM-Calibrated	RPJM-Error
Coal	47,634	46,649	-2.07%	208,980	206,627	-1.13%
Nuclear	83,200	83,384	0.22%	204,376	204,447	0.04%
Gas	72,503	73,388	1.22%	144,255	142,576	-1.16%
Hydro	2,518	2,499	-0.77%	12,350	12,497	1.19%
Wind	3,591	3,575	-0.44%	17,124	18,315	6.96%
Oil+Other	1,692	879	-45.14%	738	1,572	113.01%
Solar	70	69	-0.44%	1,399	1,933	38.16%
Biomass	1,916	2,292	19.65%	5,974	5,924	-0.84%
Total	213,034	212,736	-0.14%	595,196	593,890	-0.22%

7.2.2 Capacity Expansion

Our model's calibration results for new capacities by technology in 2017 in Pennsylvania and Rest of PJM are shown below.

Table A.15: Capacity Expansion Calibration Results in PJM in 2017.

Technology	PA-Model	PA-Actual	PRJM-Model	RPJM-Actual
NGCC	1,270	1,340	1,626	1,766
Wind	0	0	156	126
Solar	0	0	194	204

7.2.3 CO_2 Emissions

Total PJM's CO_2 emission for 2017 is taken from the Monitoring Analytics' 2017 State of the Market, which reports total CO_2 emission of 375.7 MMT. Using CO_2 emission data from 2017 EIA's State Electricity Profiles for Pennsylvania of 79.2 MMT, we can impute rest of PJM's 2016 CO_2 emission of 296.4 MMT. Our model predicts CO_2 emission 76.3 MMT in Pennsylvania, yielding an error of -3.7%. Our model's prediction of Rest of PJM's CO_2 emission is 288.1 MMT in rest of PJM, yielding an error of -2.8%. For the entire PJM, our model predicts total CO_2 emission of 364.4 MMT, which yields a 2.99% error. We slightly under-predict CO_2 emissions in both

Pennsylvania and rest of PJM.

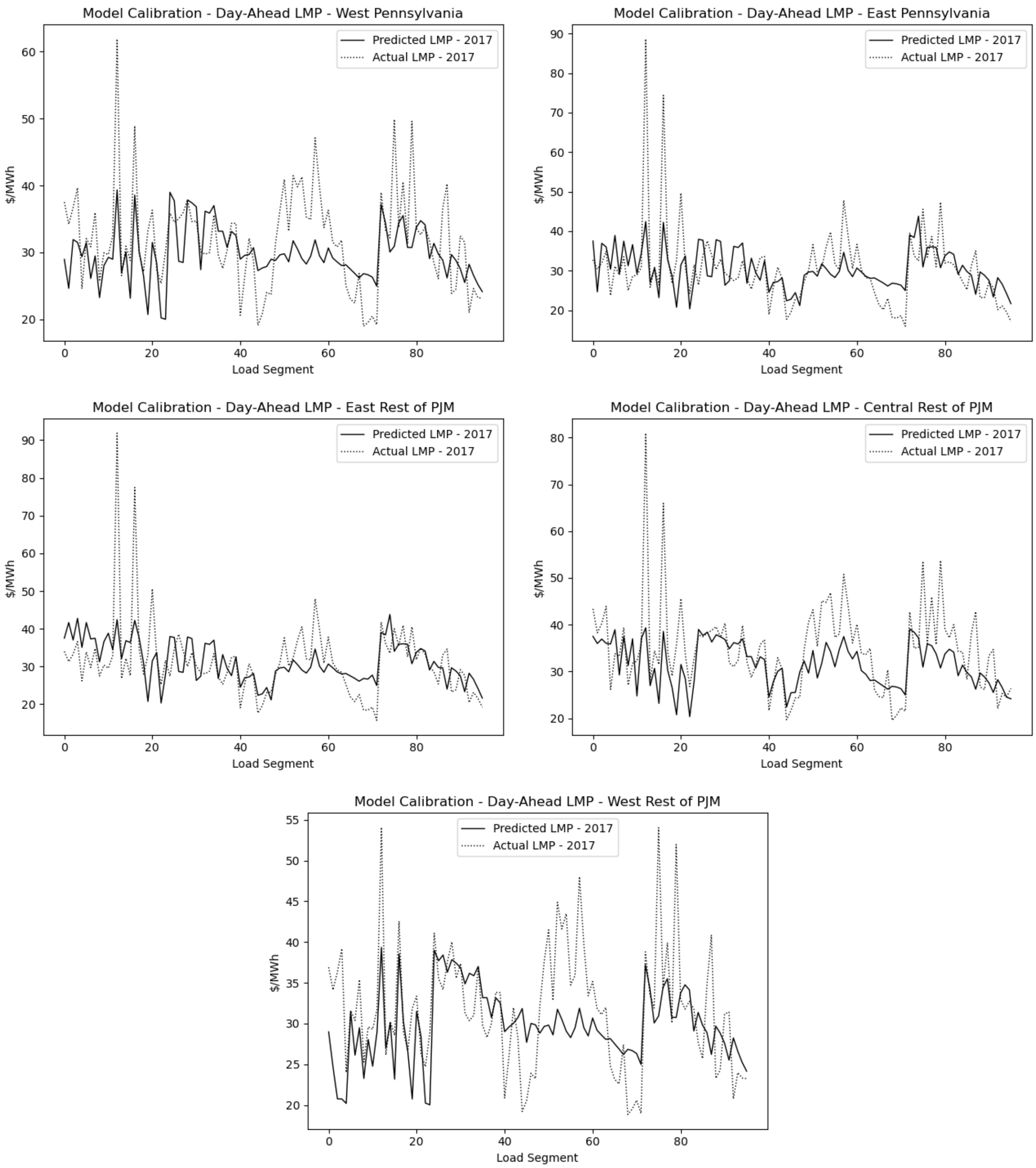
7.2.4 REC Prices

Table A.16: Calibration Results for Generation Weighted REC prices in Pennsylvania and Rest of PJM in 2017.

	PA-Actual	PA-Model	RPJM-Actual	RPJM-Model
Tier 1 Price	\$2.95	\$4.12	\$33.38	\$35.53
Tier 2 Price	\$8.44	\$11.81	\$2.89	\$3.08
SREC Price	\$0.0019	\$0.0027	\$0.35	\$0.37

7.2.5 LMP

Figure A.16: Calibration Results for Day-Ahead LMP in West Pennsylvania (Top Row, Left), East Pennsylvania (Top Row, Right), East RPJM (Second Row, Left), Central RPJM (Second Row, Right) and West RPJM (Bottom Row) in 2017. $R^2 = 0.36$



8 Model Validation Results

We validate our model using 2018 data across a few categories: load, generation mix, capacity expansion, CO_2 emissions, weighted REC prices and region-level Locational Marginal Prices (LMPs). We use PJM's actual total hourly load in 2018 and actual fuel prices from the same sources described in 3.2.2 for year 2018. Our model predicted load matches actual 2018 load with an $R^2 = 0.948$.

8.1 Generation Mix Validation

We validate the generation mix from out model using data on actual generation by fuel type reported by the Monitoring Analytics in their 2018 State of the Market report. The validation results are shown in the table below.

Table A.17: Validation Results for Total Generation in PJM in 2018 by fuel type (GWh).

Fuel	PJM-Actual	PJM-Model
Coal	239,612	229,691
Nuclear	286,115	287,678
Gas	256,701	267,483
Hydro	19,416	19,441
Wind	21,628	22,596
Oil+Other	3,581	2,480
Solar	2,111	3,192
Biomass	8,390	9,044
Total	837,594	841,605

8.2 Capacity Expansion Validation

Table A.18: Validation Results for Capacity Expansion (MW) and New Generation (GWh) in Pennsylvania and Rest of PJM in 2018 by technology.

	PA-Actual	PA-Model	RPJM-Actual	RPJM-Model
New Capacity				
NGCC	5,112	3,407	4,330	4,443
Wind	0	0	762	987
Solar	0	0	265	804
New Generation				
NGCC	43,093	28,002	36,455	36,593
Wind	0	0	1,969	2,550
Solar	0	0	395	1,198

8.3 CO_2 Emissions Validation

Total PJM's CO_2 Emission for 2018 is taken from the Monitoring Analytics' 2018 State of the Market, which reports total CO_2 Emission of 370.1 MMT. Using CO_2 emission data from 2018 EIA's State Electricity Profiles for Pennsylvania of 69.9 MMT, we can impute rest of PJM's 2018 CO_2 emission of 300.2 MMT. Our model predicts CO_2 emission 60.9 MMT in Pennsylvania, and of 291.0 MMT in rest of PJM, totaling 351.3 MMT, which yields a 5% error. We slightly under-predict CO_2 emissions in both Pennsylvania and rest of PJM.

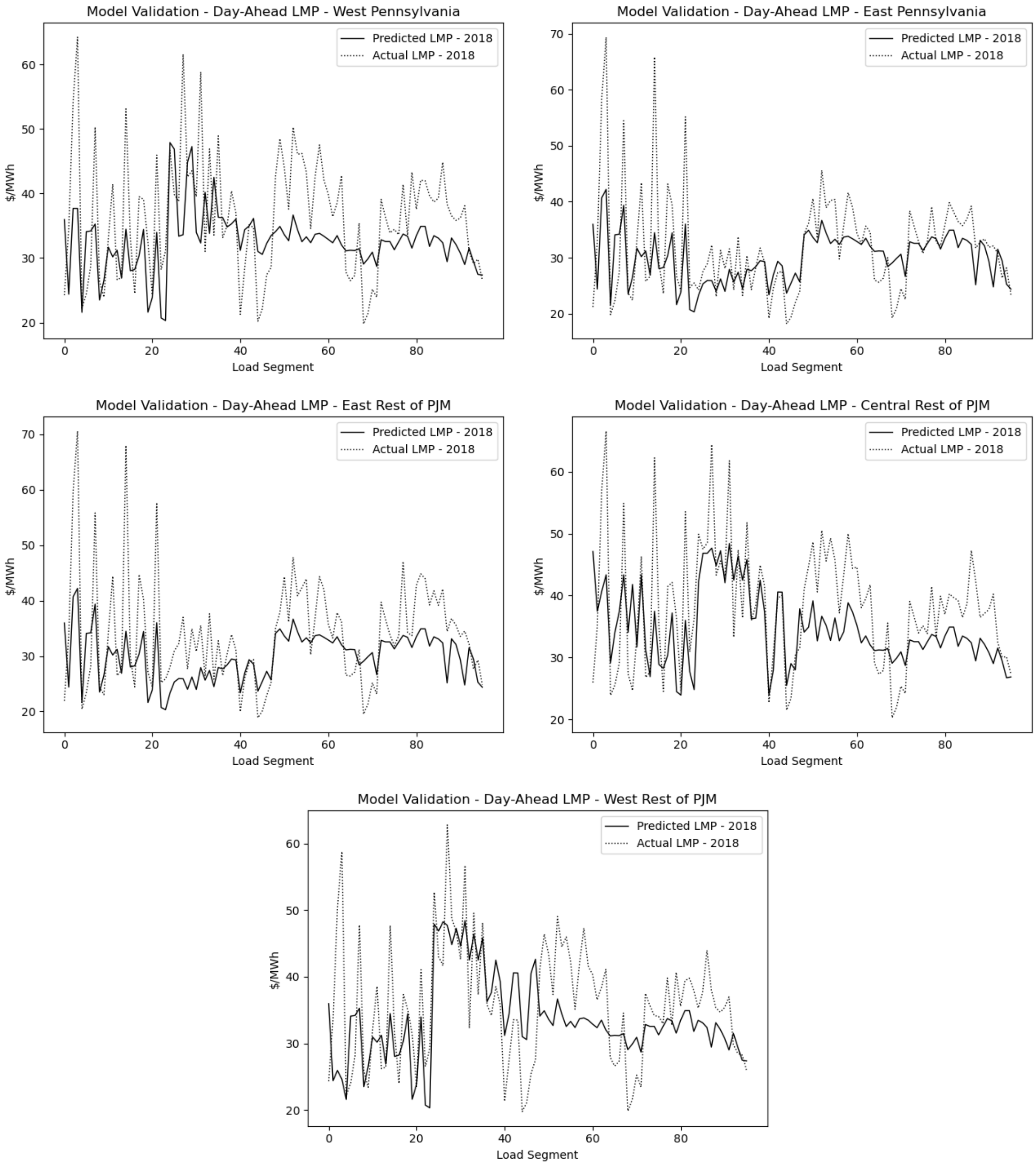
8.4 REC prices Validation

Table A.19: Validation Results for Generation Weighted REC prices in Pennsylvania and Rest of PJM in 2018.

	PA-Actual	PA-Model	RPJM-Actual	RPJM-Model
Tier 1 Price	$4.35	$4.60	$46.00	$36.39
Tier 2 Price	$12.45	$13.17	$3.99	$3.18
SREC Price	$0.0028	$0.0029	$0.48	$0.38

8.5 LMP Validation

Figure A.17: Validation Results for Day-Ahead LMP in West Pennsylvania (Top Row, Left), East Pennsylvania (Top Row, Right), East RPJM (Second Row, Left), Central RPJM (Second Row, Right) and West RPJM (Bottom Row) in 2018. $R^2 = 0.28$



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9 Additional Figures and Tables

Table A.20: Impact of Pennsylvania Joining RGGI on Capacity Expansion

	Base Case	Central Case	No RPS
Pennsylvania:			
Natural Gas - 2022 (GW)	0.00	0.00	0.00
Natural Gas - 2023 to 2025	0.00	0.00	0.00
Natural Gas - 2026	0.00	0.00	0.00
Natural Gas - 2027 to 2029	0.00	0.00	0.00
Natural Gas - 2030	0.00	0.00	0.00
Wind - 2022	0.92	0.10	0.00
Wind - 2023 to 2025	0.47	0.16	0.00
Wind - 2026	0.00	0.00	0.00
Wind - 2027 to 2029	0.00	0.00	0.00
Wind - 2030	0.00	0.05	0.00
Solar - 2022	0.00	0.00	0.00
Solar - 2023 to 2025	0.00	0.00	0.00
Solar - 2026	0.00	0.00	0.00
Solar - 2027 to 2029	0.00	0.00	0.00
Solar - 2030	0.01	0.00	0.00
Rest of PJM:			
Natural Gas - 2022 (GW)	0.00	0.00	0.00
Natural Gas - 2023 to 2025	0.00	0.00	0.00
Natural Gas - 2026	0.00	0.00	0.00
Natural Gas - 2027 to 2029	0.00	0.00	0.00
Natural Gas - 2030	0.00	0.00	0.00
Wind - 2022	0.32	0.72	0.18
Wind - 2023 to 2025	4.85	7.43	7.77
Wind - 2026	2.00	2.19	2.10
Wind - 2027 to 2029	2.18	2.26	2.45
Wind - 2030	0.94	0.50	0.66
Solar - 2022	0.15	0.19	0.18
Solar - 2023 to 2025	2.55	0.68	0.67
Solar - 2026	0.21	0.23	0.23
Solar - 2027 to 2029	0.18	0.14	0.14
Solar - 2030	0.08	0.03	0.05

Table A.21: Impact of Pennsylvania Joining RGGI on Transmission

	2022	2026	2030	Cumulative
Flow into East PA (2) from West PA (1) (1,000 GWh)	22.7	22.3	23.0	202.3
Change	2.2	3.8	5.2	35.7
Flow into Central RPJM (4) from West RPJM (5)	19.2	21.4	25.6	196.7
Change	-8.7	-6.1	-5.8	-61.9
Total Cross-Border	-69.9	-71.7	-73.3	-650.9
Change	38.4	41.6	50.6	398.1
Flow into East PA (2) from East RPJM (3)	-50.5	-50.8	-50.9	-456.9
Change	1.3	0.2	0.5	3.6
Flow into East PA (2) from Central RPJM (4)	-12.3	-12.5	-13.2	-114.8
Change	8.7	8.5	9.7	83.2
Flow into West PA (1) from West RPJM (5)	-7.2	-8.5	-9.1	-79.3
Change	28.3	33.0	40.5	311.3

Congestion Price between East PA (2) and West PA (1) - Base Case ($/MWh)	$ -0.47	$ -0.06	$ 0.02	$ -0.18
Congestion Price between East PA (2) and West PA (1) - Central Case ($/MWh)	$ -0.31	$ 0.40	$ 0.92	$ 0.31
Change	$ 0.16	$ 0.45	$ 0.90	$ 0.48
Congestion Price between Central RPJM (4) and West RPJM (5) - Base Case	$ 0.59	$ 1.34	$ 2.27	$ 1.41
Congestion Price between Central RPJM (4) and West RPJM (5) - Central Case	$ 0.04	$ 0.72	$ 1.39	$ 0.69
Change	$ -0.55	$ -0.62	$ -0.88	$ -0.72
Congestion Price Cross Border - Base Case	$ -2.76	$ -3.55	$ -4.50	$ -3.72
Congestion Price Cross Border - Central Case	$ -1.27	$ -2.24	$ -2.04	$ -2.02
Change	$ 1.50	$ 1.31	$ 2.46	$ 1.70
Congestion Price between East PA (2) and East RPJM (3) - Base Case	$ -5.30	$ -8.11	$ -9.92	$ -8.18
Congestion Price between East PA (2) and East RPJM (3) - Central Case	$ -2.61	$ -6.20	$ -5.94	$ -5.49
Change	$ 2.69	$ 1.91	$ 3.98	$ 2.69
Congestion Price between East PA (2) and Central RPJM (4) - Base Case	$ -2.02	$ -1.97	$ -2.92	$ -2.28
Congestion Price between East PA (2) and Central RPJM (4) - Central Case	$ -0.77	$ -0.42	$ -0.32	$ -0.48
Change	$ 1.25	$ 1.55	$ 2.60	$ 1.80
Congestion Price between West PA (1) and West RPJM (5) - Base Case	$ -0.96	$ -0.57	$ -0.67	$ -0.70
Congestion Price between West PA (1) and West RPJM (5) - Central Case	$ -0.42	$ -0.09	$ 0.15	$ -0.10
Change	$ 0.54	$ 0.48	$ 0.81	$ 0.60

Table A.22: Impact of Pennsylvania Joining RGGI on CO_2 Emissions in Pennsylvania Across Regions

	2022	2026	2030	Cumulative
West Pennsylvania:				
Baseline Total CO_2 Emissions (MMT CO_2)	48.8	50.1	52.2	455.0
Change	-23.0	-25.6	-30.9	-241.4
Baseline Covered CO_2 Emissions	48.4	49.7	51.8	451.8
Change	-23.1	-25.6	-30.9	-241.8
Baseline Uncovered CO_2 Emissions	0.4	0.4	0.4	3.2
Change	0.0	0.1	0.1	0.5
East Pennsylvania:				
Baseline Total CO_2 Emissions (MMT CO_2)	40.7	41.9	43.2	378.1
Change	-9.2	-9.1	-11.8	-91.6
Baseline Covered CO_2 Emissions	40.3	41.6	42.9	375.4
Change	-9.3	-9.2	-12.0	-93.1
Baseline Uncovered CO_2 Emissions	0.4	0.3	0.3	2.7
Change	0.1	0.2	0.2	1.5

Table A.23: Impacts of Pennsylvania Removing AEPS on REC Markets.

	2022	2026	2030	Cumulative
Pennsylvania:				
REC Price Tier 1 Under Central Case ($/MWh)	$ 27.14	$ 20.66	$ 17.05	$ 21.22
Change	$-27.14	$-20.66	$-17.05	$-21.22
REC Price Tier 2 Under Central Case	$ 0.00	$ 0.00	$ 0.00	$ 0.00
Change	$ -0.00	$ -0.00	$ -0.00	$ -0.00
SREC Price Under Central Case	$ 0.00	$ 0.00	$ 0.00	$ 0.00
Change	$ -0.00	$ -0.00	$ -0.00	$ -0.00
RPS Tier 1 Target	0.08	0.08	0.08	0.08
RPS Tier 2 Target	0.10	0.10	0.10	0.10
SRPS Target	0.01	0.01	0.01	0.01
Rest of PJM:				
REC Price Tier 1 Under Central Case ($/MWh)	$ 13.69	$ 14.00	$ 11.49	$ 13.35
Change	$ -0.27	$ -0.01	$ 0.24	$ -0.03
REC Price Tier 2 Under Central Case	$ 0.00	$ 0.00	$ 0.00	$ 0.00
Change	$ -0.00	$ 0.00	$ -0.00	$ -0.00
SREC Price Under Central Case	$ 11.04	$ 9.60	$ 8.54	$ 9.70
Change	$ -0.02	$ 0.56	$ -0.48	$ 0.27
RPS Tier 1 Target	0.10	0.14	0.15	0.13
RPS Tier 2 Target	0.00	0.00	0.00	0.00
SRPS Target	0.01	0.01	0.01	0.01

Table A.24: Impact of Pennsylvania Removing AEPS on CO_2 Emissions in Pennsylvania Across Regions.

	2022	2026	2030	Cumulative
West Pennsylvania:				
Total Emissions Under Base Case (MMT)	25.8	24.5	21.3	213.6
Change	4.3	2.2	-0.0	19.9
Total Covered Emissions Under Base Case	25.4	24.1	20.9	209.9
Change	4.4	2.3	-0.0	20.3
Total Uncovered Emissions Under Base Case	0.4	0.4	0.4	3.7
Change	-0.1	-0.0	-0.0	-0.4
East Pennsylvania:				
Total Emissions Under Base Case (MMT)	31.5	32.8	31.4	286.5
Change	3.6	2.9	0.5	22.9
Total Covered Emissions Under Base Case	31.1	32.3	30.9	282.3
Change	3.8	3.0	0.5	24.0
Total Uncovered Emissions Under Base Case	0.5	0.4	0.5	4.2
Change	-0.1	-0.1	-0.1	-1.1

Table A.25: Impact of Pennsylvania Removing AEPS on CO_2 Emissions.

	2022	2026	2030	Cumulative
Pennsylvania:				
Total CO_2 Emissions Under Central Case (MMT)	57.3	57.3	52.8	500.1
Change	8.0	5.1	0.4	42.8
Covered CO_2 Emissions Under Central Case	56.4	56.4	51.8	492.2
Change	8.2	5.3	0.5	44.3
Uncovered CO_2 Emissions Under Central Case	0.9	0.9	0.9	7.9
Change	-0.2	-0.2	-0.1	-1.5
RGGI Emissions Cap Upon Joining RGGI	70.8	61.7	52.7	555.5
Rest of PJM States in RGGI:				
Total CO_2 Emissions Under Central Case (MMT)	69.0	67.1	65.5	602.7
Change	-2.7	-1.5	-3.6	-18.8
Covered CO_2 Emissions Under Central Case	67.1	65.2	63.5	585.1
Change	-2.7	-1.6	-3.7	-19.1
Uncovered CO_2 Emissions Under Central Case	1.9	1.9	2.0	17.6
Change	0.0	0.0	0.0	0.2
Emission Cap	43.5	50.5	43.3	396.7
Non-PJM States in RGGI:				
Covered CO_2 Emissions Under Central Case (MMT)	42.0	39.9	28.8	334.4
Change	-2.5	-1.7	-8.7	-25.2
RGGI Emission Cap	46.6	42.3	36.3	374.6
Rest of PJM States Not in RGGI:				
Uncovered CO_2 Emissions Under Central Case (MMT)	252.8	243.4	256.1	2251.1
Change	-4.5	-3.8	3.5	-21.5
Emission Leakage:				
Intended Emission Reduction Compared to Base Case (MMT)	18.0	29.6	42.0	271.6
Actual Emission Reduction	1.2	6.8	13.7	60.7
Leakage	16.8	22.7	28.3	210.9
Leakage Ratio	0.94	0.77	0.67	0.78
Banking Permits:				
Total Banked Permits Withdrawn Under Central Case (MMT)	-4.7	-13.9	-23.7	-84.9
Change	-3.0	-2.0	11.8	-0.0
Permit Price Under Central Case ($/MT)	5.44	6.06	9.38	6.89
Change	0.73	0.52	2.59	0.84

Table A.26: Impact of Pennsylvania Removing on the Change in Total External Costs From CO_2 Emissions Reductions, Compared to Base Case.

	2022	2026	2030	Cumulative*
Change in CO_2 Emission (MMT)	-1.2	-6.8	-13.7	-60.7
Change in CO_2 External Costs (million $)	-58.9	-381.4	-884.2	-3053.8

Notes: * net present value reported over 2022-2030 in 2016 $ assuming market discount rate of 3.0.

Table A.27: Impacts of Pennsylvania Removing AEPS on PJM Electricity Market.

	2022	2026	2030	Cumulative
Pennsylvania:				
Average Electricity Price* under Central Case ($/MWh) ($/MWh)	$ 34.85	$ 34.97	$ 36.37	$ 35.35†
Change	$ -0.72	$ -0.55	$ 0.48	$ -0.43†
Net Imports Under Central Case (1,000 GWh)	-31.6	-30.1	-22.7	-252.9
Change	-10.9	-6.9	-0.8	-56.8
Demand Under Central Case (1,000 GWh)	160.3	162.9	165.4	1465.8
Change	0.2	0.2	-0.1	1.0
Total Generation Under Central Case	202.8	204.1	199.1	1818.3
Change	11.6	7.3	0.6	60.8
Existing Generation Under Central Case	202.5	203.5	198.4	1812.4
Change	11.9	8.0	1.5	67.2
New Generation Under Central Case	0.3	0.7	0.8	6.0
Change	-0.3	-0.7	-0.8	-6.0
AEC Price Under Central Case, Tier 1 ($/MWh)	$ 27.14	$ 20.66	$ 17.05	$ 21.22†
Change	$-27.14	$-20.66	$-17.05	$-21.22†
AEPS Tier 1 Target	0.08	0.08	0.08	0.08
Rest of PJM:				
Average Electricity Price* under Central Case ($/MWh)	$ 36.10	$ 37.29	$ 38.59	$ 37.44†
Change	$ -0.25	$ -0.12	$ 0.78	$ -0.02†
Net Imports Under Central Case (1,000 GWh)	31.6	30.1	22.7	252.9
Change	10.9	6.9	0.8	56.8
Demand Under Central Case (1,000 GWh)	657.0	667.9	678.7	6010.7
Change	0.4	0.3	-0.6	1.5
Total Generation Under Central Case	667.9	681.1	700.2	6147.8
Change	-11.1	-6.8	-1.3	-58.1
Existing Generation Under Central Case	665.8	652.0	663.5	5936.8
Change	-9.6	-6.1	-1.6	-52.6
New Generation Under Central Case	2.2	29.1	36.6	210.8
Change	-1.4	-0.8	0.2	-5.9
Average REC Price Under Central Case**, Tier 1 ($/MWh)	$ 13.69	$ 14.00	$ 11.49	$ 13.35†
Change	$ -0.27	$ -0.01	$ 0.24	$ -0.03†
Average RPS Tier 1 Target**	0.10	0.14	0.15	0.13

Notes: * reflects load weighted average. ** reflects generation weighted average. † reflects average across all years 2022-2030.

Table A.28: Impacts of Pennsylvania Removing AEPS on Transmission.

	2022	2026	2030	Cumulative
Flow into East PA (2) from West PA (1) (1,000 GWh)	24.9	26.1	28.2	238.0
Change	-1.7	-1.7	0.1	-12.8
Flow into Central RPJM (4) from West RPJM (5)	10.5	15.3	19.8	134.7
Change	1.2	-0.2	1.7	3.1
Total Cross-Border	-31.6	-30.1	-22.7	-252.9
Change	-10.9	-6.9	-0.8	-56.8
Flow into East PA (2) from East RPJM (3)	-49.2	-50.6	-50.4	-453.2
Change	-0.6	-0.1	-0.1	-1.9
Flow into East PA (2) from Central RPJM (4)	-3.5	-4.0	-3.6	-31.6
Change	-3.4	-2.4	-0.9	-18.9
Flow into West PA (1) from West RPJM (5)	21.1	24.5	31.3	232.0
Change	-6.9	-4.4	0.3	-36.0

Congestion Price between East PA (2) and West PA (1) - Central Case ($/MWh)	$ -0.31	$ 0.40	$ 0.92	$ 0.31
Congestion Price between East PA (2) and West PA (1) - no RPS ($/MWh)	$ -0.41	$ 0.25	$ 1.10	$ 0.24
Change	$ -0.11	$ -0.15	$ 0.18	$ -0.07
Congestion Price between Central RPJM (4) and West RPJM (5) - Central Case	$ 0.04	$ 0.72	$ 1.39	$ 0.69
Congestion Price between Central RPJM (4) and West RPJM (5) - no RPS	$ -0.04	$ 0.73	$ 1.81	$ 0.75
Change	$ -0.08	$ 0.01	$ 0.43	$ 0.06
Congestion Price Cross Border - Central Case	$ -1.27	$ -2.24	$ -2.04	$ -2.02
Congestion Price Cross Border - no RPS	$ -1.74	$ -2.69	$ -2.29	$ -2.44
Change	$ -0.48	$ -0.45	$ -0.25	$ -0.42
Congestion Price between East PA (1) and East RPJM (3) - Central Case	$ -2.61	$ -6.20	$ -5.94	$ -5.49
Congestion Price between East PA (2) and East RPJM (3) - no RPS	$ -3.52	$ -7.15	$ -6.50	$ -6.36
Change	$ -0.91	$ -0.95	$ -0.56	$ -0.87
Congestion Price between East PA (2) and Central RPJM (4) - Central Case	$ -0.77	$ -0.42	$ -0.32	$ -0.48
Congestion Price between East PA (2) and Central RPJM (4) - no RPS	$ -1.04	$ -0.70	$ -0.54	$ -0.73
Change	$ -0.28	$ -0.28	$ -0.22	$ -0.26
Congestion Price between West PA (1) and West RPJM (5) - Central Case	$ -0.42	$ -0.09	$ 0.15	$ -0.10
Congestion Price between West PA (1) and West RPJM (5) - no RPS	$ -0.67	$ -0.21	$ 0.17	$ -0.23
Change	$ -0.25	$ -0.12	$ 0.03	$ -0.13

Table A.29: Economic Impacts of Pennsylvania Removing AEPS on East and West Pennsylvania.

	2022	2026	2030	Cumulative*
West Pennsylvania:				
Net Economic Benefit Under Central Case (billion $)	$ 20.7	$ 20.9	$ 21.6	$ 169.1
Change (million $)	$ -47.1	$ -31.1	$ 28.3	$-199.4
From Participation in PJM Electricity Market	$ -24.7	$ -17.2	$ 27.2	$ -86.6
From Benefits to Ratepayers	$ 20.5	$ 13.0	$ -27.9	$ 83.4
From Benefits to Generators**, Producer Surplus	$ -45.2	$ -30.2	$ 55.1	$-170.0
From Covered Generators	$ -45.5	$ -24.8	$ 60.0	$-134.6
From Uncovered Generators	$ 0.3	$ -5.4	$ -4.9	$ -35.4
From Participation in RGGI Allowance Market	$ -22.3	$ -13.9	$ 1.2	$-112.8
From Cost of Permits Bought	$ -45.7	$ -27.5	$ -53.8	$-277.6
From Value of Permits Auctioned †	$ 23.4	$ 13.6	$ 55.0	$ 164.8
East Pennsylvania:				
$W_{PA-East}$, Baseline Net Economic Benefit (billion $)	$ 34.0	$ 34.6	$ 35.8	$ 278.8
Change (million $)	$ -35.8	$ -23.4	$ 6.0	$-174.2
From Participation in PJM Electricity Market	$ -18.2	$ -5.1	$ 10.9	$ -39.4
From Benefits to Ratepayers	$ 45.8	$ 37.8	$ -67.2	$ 201.6
From Benefits to Generators**	$ -64.1	$ -42.9	$ 78.1	$-241.0
From Covered Generators	$ -64.5	$ -35.2	$ 85.0	$-190.8
From Uncovered Generators	$ 0.4	$ -7.7	$ -6.9	$ -50.2
From Participation in RGGI Allowance Market	$ -17.6	$ -18.3	$ -4.9	$-134.8
From Cost of Permits Bought	$ -46.2	$ -36.6	$ -86.2	$-358.2
From Value of Permits Auctioned †	$ 28.6	$ 18.3	$ 81.3	$ 223.4

Notes: * net present value reported over 2022-2030 in 2016 $ assuming market discount rate of 3.0 %. ** excludes cost of permits bought. † permit revenues are allocated across the two Pennsylvania regions in proportion to the shares in cost of permits bought in each region

Table A.30: Aggregate Surplus from Pennsylvania Removing AEPS.

	2022	2026	2030	Cumulative*
A. Transmission Lines Within and Between Regions:				
Net Benefits to Transmission Owners under Central Case (billion $)	$ 0.5	$ 0.6	$ 0.7	$ 4.9
Change (million $)	$ 58.1	$ 28.8	$ 67.5	$ 326.3
From Lines in Pennsylvania	$ 1.9	$ -8.7	$ 21.2	$ -2.0
From Lines in Rest of PJM	$ 9.2	$ -5.5	$ 20.6	$ 2.4
From Lines Between PA and RPJM	$ 47.1	$ 43.0	$ 25.7	$ 325.9
B. Pennsylvania:				
Net Economic Benefit (billion $)	$ 54.7	$ 55.5	$ 57.4	$ 447.8
Change (million $)	$ -82.8	$ -54.5	$ 34.3	$-373.6
From Participation in PJM Electricity Market	$ -42.9	$ -22.3	$ 38.0	$-126.0
From Benefits to Ratepayers	$ 66.3	$ 50.8	$ -95.1	$ 285.0
From Benefits to Generators**	$-109.3	$ -73.1	$ 133.2	$-411.0
From Covered Generators	$-110.0	$ -60.0	$ 145.0	$-325.5
From Uncovered Generators	$ 0.7	$ -13.1	$ -11.8	$ -85.5
From Participation in RGGI Allowance Market	$ -39.9	$ -32.2	$ -3.7	$-247.5
From Cost of Permits Bought	$ -91.9	$ -64.1	$-140.0	$-635.7
From Value of Permits Auctioned	$ 52.0	$ 31.9	$ 136.3	$ 388.2
Change in Net Economic Benefit to Pennsylvania + Benefits to Trans. Own. From PA Lines	$ -81.0	$ -63.2	$ 55.5	$-375.6
Change in Net Economic Benefit to Pennsylvania + Benefits to Trans. Own. From PA and PA–RPJM Lines	$ -33.9	$ -20.2	$ 81.2	$ -49.7
C. Rest of PJM States in RGGI:				
Net Economic Benefit under Central Case (billion $)	$ 98.0	$ 99.6	$ 102.7	$ 803.0
Change (million $)	$ 68.1	$ 52.4	$ -50.6	$ 263.6
From Participation in PJM Electricity Market	$ 68.8	$ 49.8	$ -42.1	$ 265.4
From Benefits to Ratepayers	$ 119.3	$ 91.4	$-171.2	$ 512.7
From Benefits to Generators**	$ -50.6	$ -41.6	$ 129.1	$-247.3
From Covered Generation	$ -50.1	$ -39.5	$ 144.5	$-218.2
From Uncovered Generation	$ 33.5	$ -0.1	$ -22.1	$ -33.4
From Participation in RGGI Allowance Market	$ -0.6	$ 2.6	$ -8.5	$ -1.8
From Cost of Permits Bought	$ -32.6	$ -23.5	$-120.4	$-285.6
From Value of Permits Auctioned	$ 31.9	$ 26.1	$ 112.0	$ 283.8
D. Non-PJM States in RGGI:				
Net Economic Benefit under Central Case (billion $)	$ 0.5	$ 0.5	$ 0.5	$ 4.0
Change (million $)	$ 4.2	$ 1.7	$ 30.6	$ 47.8
From Reduced CO_2 Abatement Costs	$ -14.3	$ -11.0	$ -92.7	$-176.4
From Participation in RGGI Allowance Market	$ 18.6	$ 12.7	$ 123.3	$ 224.2
From Cost of Permits Bought	$ -15.7	$ -9.2	$ 29.4	$ -38.3
From Value of Permits Auctioned	$ 34.2	$ 21.9	$ 93.9	$ 262.6

Notes: * net present value reported over 2022-2030 in 2016 $ assuming market discount rate of 3.0 %. ** excludes cost of permits bought by generators.

Table A.31: Aggregate Surplus from Pennsylvania Removing AEPS.

	2022	2026	2030	Cumulative
E. Rest of PJM States not in RGGI:				
Net Econ. Ben. From Partic. in PJM (billion $) under Central Case (billion $)	$ 143.3	$ 144.8	$ 149.0	$1168.7
Change (million $)	$ 6.8	$ 15.9	$ -64.4	$ 59.0
From Participation in PJM Electricity Market	$ 6.8	$ 15.9	$ -64.4	$ 59.0
From Benefits to Ratepayers	$ 173.3	$ 132.7	$-248.6	$ 744.7
From Benefits to Generators	$-166.5	$-116.8	$ 184.2	$-685.7

F. Holders of Allowances Banked Prior to 2022:				
Net Economic Benefit under Central Case (billion $)	$ 0.0	$ 0.2	$ 0.1	$ 1.1
Change (million $)	$ 22.1	$ 1.6	$-111.1	$ 16.1
From Value of Banked Permits	$ 0.1	$ -15.3	$ -0.0	$ -9.0
From Cost of Permits Bought in RGGI Allow. Market	$ 22.0	$ 16.9	$-111.1	$ 25.1
From Cost of Permits Bought	$ 22.0	$ 16.9	$-111.1	$ 25.1
From Value of Permits Auctioned	$ 0.0	$ 0.0	$ 0.0	$ 0.0

G. PJM:				
Net Economic Benefit† under Central Case (billion $)	$ 296.5	$ 300.5	$ 309.7	$2424.3
Change (million $)	$ 50.2	$ 42.6	$ -13.2	$ 275.3
From Participation in PJM Electricity Market	$50.2	$ 13.1	$-13.2	$-414.7
From Benefits to Transmission Owners	$ 58.1	$ 28.8	$ 67.5	$ 326.3
From Pennsylvania	$ -82.8	$ -54.5	$ 34.3	$-373.6
From Rest of PJM States in RGGI	$ 68.1	$ 52.4	$ -50.6	$ 263.6
From Rest of PJM States Not in RGGI	$ 6.8	$ 15.9	$ -64.4	$ 59.0
dW^e_{PJM}, From PJM Permit Market	$ -40.5	$ -29.5	$ -12.2	$-249.4

H. PJM and Non-PJM States in RGGI:				
Net Economic Benefit under Central Case (billion $)	$ 297.1	$ 301.2	$ 310.3	$2429.3
Change (million $)	$ 76.5	$ 45.9	$ -93.6	$ 339.2
From Participation in PJM Electricity Market	$ 32.6	$ 43.4	$ -68.5	$ 198.4
From Pennsylvania	$ -42.9	$ -22.3	$ 38.0	$-126.0
From Rest of PJM States in RGGI	$ 68.8	$ 49.8	$ -42.1	$ 265.4
From Rest of PJM States Not in RGGI	$ 6.8	$ 15.9	$ -64.4	$ 59.0
From Benefits to Transmission Owners	$ 58.1	$ 28.8	$ 67.5	$ 326.3
From Participation in RGGI Allowance Market	$ 0.0	$ -0.0	$ 0.0	$ -0.0
From Pennsylvania	$ -39.9	$ -32.2	$ -3.7	$-247.5
From Rest of PJM States in RGGI	$ -0.6	$ 2.6	$ -8.5	$ -1.8
From RGGI States Not in PJM	$ 18.6	$ 12.7	$ 123.3	$ 224.2
From Holders of Banked Allowances	$ 22.0	$ 16.9	$-111.1	$ 25.1
From Reduced CO_2 Abatement Costs	$ -14.3	$ -11.0	$ -92.7	$-176.4
From Value of Banked Permits	$ 0.1	$ -15.3	$ -0.0	$ -9.0

Notes: * net present value reported over 2022-2030 in 2016 $ assuming market discount rate of 3.0 %. ** excludes cost of permits bought by generators. † excludes the value of banked permits.