The Role of Output Reallocation and Investment in Coordinating Externality Markets

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Abstract

We empirically measure the inefficiency of uncoordinated externality markets in the context of CO_2 regulation of electricity generation. Using data from a large regional U.S. wholesale electricity market that spans multiple states, we estimate a dynamic structural model of production and investment, and simulate the model under two scenarios to measure the inefficiency. In the first scenario, plants face CO_2 prices that differ across states. In the second scenario, plants face a single CO_2 price. Holding investment in new plant capacity fixed, generation costs in the first scenario can be as high as $7.8 billion, or about 50% of the cost of complying with the regulation, relative to the second scenario. However, we find that the inefficiency with uncoordinated CO_2 markets is eliminated once we allow for optimal investment.

Keywords: Optimal Investment, Uncoordinated Regulation, Emissions Markets, Empirical Games.

JEL codes: L1, L5, L9, Q4, Q5.

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1 Introduction

Product markets typically fail in the presence of externalities. Since the work of Coase, economists have known that a solution to the externality problem is to establish property rights and let agents negotiate. In the presence of multiple heterogenous agents, market-based mechanisms (henceforth, "markets for the externality") can provide cost-effective solutions. These mechanisms put a price on the externality and efficiently coordinate behavior.

In the case of pollution, several market-based mechanisms have been developed by policy makers to correct the negative externality, including markets for emissions permits. A market for permits is an efficient way to correct the negative externality by equating heterogeneous marginal abatement costs. To maximize the gains from trade, a single market for the externality is generally ideal.[1] In practice, organizing a single externality market requires coordination of regulations across multiple jurisdictions, which is generally difficult due to differences in preferences and priorities of these jurisdictions. At best, jurisdictions that want to adopt regulation run separate and often uncoordinated externality markets. For example, there are 27 jurisdictions currently implementing or are scheduled to implement a form of carbon emissions trading system as of 2019. Moreover, most of these markets are only at the provincial or city level and are not linked to each other.[2] In the U.S., attempts to federally address greenhouse gas emissions have largely failed, and unless new legislation is passed, further attempts on regulation will most likely have to be implemented at the state level.[3]

The goal of the paper is to empirically measure outcomes under uncoordinated externality markets and compare them with outcomes under a single market. Our key insight is that uncoordinated externality markets increase firms' incentives to invest in new capacity, which mitigates the inefficiencies from lack of coordination. Given that uncoordinated regulation entails spatial dispersion in externality prices, there are locations where it is cheaper to

[1]If the marginal damage from the externality differs across jurisdictions such as in the case of NOx emissions (Muller and Mendelsohn (2009); Fowlie and Muller (2017)), then having separate *but coordinated* externality markets would be ideal from a welfare standpoint. However, the benefit of having differentiated NOx prices seem to be second order relative to having correct expectations on what abatement costs will be in the future (Fowlie and Muller (2017); Holland and Yates (2015)). In any case, we look at CO_2 emisions which is uniformly mixed unlike NOx. For uniformly mixed pollutants, the damage depends on the total emissions entering the atmosphere and not the location of the source.

[2]Among these jurisdictions, one is supranational (European Union), four are at the country level (China, Colombia, New Zealand, Switzerland), fifteen are provinces and states, and seven are cities. See https://icapcarbonaction.com/ets-map for an updated interactive map of emissions trading systems in force, scheduled or under consideration at the national and subnational levels.

[3]Absent new legislation, efforts to regulate CO_2 will fall under the purview of the Clean Air Act (Goulder and Stavins, 2010). The Act authorizes the Environmental Protection Agency (EPA) to set state-level targets and solicit state implementation plans to achieve these targets. While the EPA can encourage coordination among states, it does not have the power to force them to do so.

emit. All else equal, profit-maximizing firms will move production (and emissions) towards these locations until there is no dispersion in prices, or once capacity constraints in low-priced locations impede reallocation. Binding capacity constraints induces an additional benefit to investing in new capacity since new capacity relaxes these constraints and allow further reallocation. This additional benefit to investing is thus driven by the desire to reallocate production that arises because of dispersion in prices, hence is only present under uncoordinated externality markets.

We take CO_2 emissions regulation of electricity generating plants as our empirical setting. The electricity sector is a major source of CO_2 emissions, just behind transportation, and efforts to control emissions often directly target the industry. We focus on the set of plants participating in the Pennsylvania-New Jersey-Maryland (PJM) wholesale electricity market, which is the world's largest wholesale electricity market covering (all or parts of) thirteen states. PJM is an ideal setting to study inefficiencies with uncoordinated CO_2 markets since there is considerable heterogeneity in the plants' fuel mix and emissions, resulting in substantial differences in the stringency of CO_2 regulation across states. Due to the heterogeneity in stringency, there are gains from trade from having a regional CO_2 market.

Using rich plant-level data, we set-up and estimate a dynamic structural model of multi-plant production and investment preserving the heterogeneity within and across firms. We simulate the model under two scenarios: (1) uncoordinated state-by-state CO_2 markets, and (2) a single PJM-wide regional CO_2 market. In the first scenario, each state is required to keep CO_2 emissions below a specified target, while in the second scenario, states comply as a region and hence are only required to keep the sum of CO_2 emissions across states to be below the sum of the individual state targets. Thus, in the first scenario plants pay a CO_2 price that depends on the location of the plant. In contrast, plants pay a single CO_2 price regardless of their location in the second scenario.[4]

Given the heterogeneity in plant characteristics and regulatory stringency across states, state-by-state CO_2 prices will likely differ. In this case, marginal abatement costs of plants will not be equal, and hence, creating inefficiency. Insights from the trade literature (e.g. Samuelson (1948) and Mundell (1957)), however, tell us that if we think about emissions as a factor of production, then inefficiencies arising from the lack of a single CO_2 market may not be that large if firms face an integrated *product* (electricity in our case) market and can reallocate production (hence emissions) across jurisdictions. In our setting, while firms own and operate plants located in different states and are subject to different CO_2 prices, these

[4]We take the CO_2 emissions targets from the Obama-era Clean Power Plan (CPP). Although the CPP has already been repealed by the Trump administration, it serves as a useful example of what CO_2 emissions regulations based on the Clean Air Act would look like.

plants supply electricity to an integrated product market, i.e. the PJM wholesale market. All else equal, profit-maximizing firms move production from plants in states with high CO_2 prices to states with low CO_2 prices. In fact, the larger the difference in CO_2 prices, the stronger the incentive to reallocate production.

Absent any frictions to output reallocation and CO_2 price adjustment, a firm will continue to reallocate output until CO_2 prices converge, as if there was a regional CO_2 market. In practice, there are important frictions that impede reallocation and sustain the inefficiency of separate externality markets. One important friction that we focus on are capacity constraints.

To understand the importance of capacity constraints, we first compute the difference in electricity generation cost between the state-by-state and regional scenarios holding capacities fixed. We refer to the difference in cost in this case as *static* inefficiency. Next, we investigate whether optimal investment differs between the two scenarios. The comparison in cost in this case will take into account potential differences in the incentives to invest, and therefore different levels of capacity. The difference in cost between the state-by-state and regional scenarios when we take optimal investment into account is a measure of *dynamic* inefficiency. Figure 1 illustrates the difference between static and dynamic inefficiency.[5]

Our results show that static inefficiency can be as much as $7.8 billion, which is about 50% of the cost of complying with the CO_2 regulation. Moreover, once we reach a sufficiently large capacity, static inefficiency disappears. For sufficiently large capacity, the capacity constraint no longer binds and thus we are back to the case of perfect reallocation. In this case, outcomes with a regional and state-by-state CO_2 markets will be the same.

Once we take optimal investment into account, we find that capacity is larger with state-by-state CO_2 markets. Since investment in new capacity facilitates reallocation of production when capacity constraints bind, there is an additional benefit to investing in new capacity which is increasing in the dispersion of CO_2 prices. This additional incentive to invest is not present in the regional scenario since CO_2 prices across states are the same. In our simulations, the additional investment in the state-by-state scenario is sufficiently large such that generating cost actually falls below the regional scenario, and thus there is no dynamic

[5] In the figure, the horizontal axis is the amount of capacity in the low CO_2 price state. The black curve represents generation cost with separate CO_2 markets, while the grey curve corresponds to the single CO_2 market scenario. At some level of capacity K, generation cost with separate markets is $C_{sep}(K)$ while the corresponding cost with single market is $C_{sin}(K)$. Thus static inefficiency at K is equal to $C_{sep}(K)-C_{sin}(K)$. Dynamic inefficiency instead takes into account potentially different levels of capacity between the state-by-state and regional scenarios. In panel (b) of Figure 1, $C_{sep}K^{**}$ is the cost corresponding to the state-by-state scenario given optimal capacity K^{**}, while $C_{sin}(K^*)$ is the cost for the regional scenario given optimal capacity K^*. The dynamic inefficiency is the difference $C_{sep}(K^{**})-C_{sin}(K^*)$, which is lower than the static inefficiency holding K fixed at K^*, i.e. $C_{sep}(K^{**})-C_{sin}(K^*) < C_{sep}(K^*)-C_{sin}(K^*)$.

inefficiency with state-by-state. Moreover, we find that decline in generation cost driven by larger investment with state-by-state CO_2 markets is larger in magnitude than than the cost from the higher level of investment, hence total cost is actually lower under the state-by-state scenario. Finally, if capacity is below the socially optimal level such as when firms have market power (e.g. McRae and Wolak (2019)), our results suggest that welfare under state-by-state CO_2 markets can even dominate welfare under a regional market.

Related Literature

Our paper is related to the literature on incomplete regulation. Incomplete regulation occurs when there is no uniform adoption of regulations across jurisdictions, hence exempting a subset of polluting sources from regulation. As such, separate and uncoordinated externality markets can be a direct consequence of incomplete regulation. The literature has focused on the important problem of emissions leakage whereby firms relocate production (and emissions) to unregulated jurisdictions, which reduces the efficacy of the regulation (see, e.g., Fowlie (2009) and Fowlie et al. (2016)). A similar form of leakage occurs when firms face overlapping state and federal regulations in only a subset of states and state regulations are stricter than federal ones (Goulder et al. (2012); Goulder and Stavins (2010)).[6]

We contribute to the literature by illustrating the importance of thinking about adjustments that may not happen in the short-run and showing how ignoring these may overstate problems with incomplete regulation.[7] Although the short-run static inefficiency with uncoordinated externality markets can be substantial, what drives the inefficiency, i.e. different state-by-state CO_2 prices, actually encourages greater investment. Greater investment in turn mitigates the inefficiency with uncoordinated markets. In fact, if there are distortions that lead to under-investment (e.g. strategic capacity withholding and lax environmental regulations), long-run welfare may end up being higher.

The paper is also germane to the literature that investigates the interaction between

[6] Bushnell et al. (2017b) study differences in regulatory environment across states resulting from lack of coordination and strategic policy choice. They study a state-level policy choice in the context of the CPP: whether to implement a mass- or a rate-based target. They show that states can strategically choose between these two policies in a way that leads to lower welfare and increased emissions (due to leakage), hence highlighting the importance of coordinating regulation. In contrast, we take a step back from the specific design of the policy, and focus on the question of single versus separate markets.

[7] There are actually two adjustments in the paper: firms adjust their capacity to facilitate further reallocation when capacity constraints bind, and, CO_2 prices across markets adjust as production (and emissions) is moved from one location to another. By assuming implementation of CO_2 regulations via markets, we are, in a way, assuming that states without any regulation—as in the typical case of incomplete regulation—will eventually impose one as emissions are dumped into the state. One example of this type of regulatory adjustment is how California's more stringent fuel efficiency standards eventually led to adoption of similar standards by other states.

environmental regulation and other forms of regulation and market structure.[8] Our work is most related to Ryan (2012) and Fowlie et al. (2016) which build a Markov Perfect Nash Equilibrium (MPNE) framework and use a two-step estimation method based on Bajari et al. (2007) to study the effects of environmental regulation in an oligopoly setting.

In terms of estimation, we closely follow the methods used in Ryan (2012) and Fowlie et al. (2016), and adapt these to fit the electricity industry and our institutional setting. One important difference is that we only need to estimate investment costs since production costs can be computed directly from data on plant-level heat rates, emission rates for various pollutants, and other operations-and-maintenance related costs (e.g., Mansur (2007), Bushnell et al. (2008) and Gowrisankaran et al. (2016)). Finally, the approach we use to solve the counterfactual simulations significantly differs from Ryan (2012) and Fowlie et al. (2016) in two ways. First, the computation of the stage game equilibrium is more involved since we need to find the set of prices that simultaneous clear more than ten markets (individual states' CO_2 markets and the main electricity market). Second, given the stage game equilibrium payoffs for each point in the state space, we solve for the MPNE by combining an upwind Gauss-Seidel approach (Judd, 1998) with a statewise Nash Equilibrium approach.[9] This approach is less prone to convergence issues since finding the MPNE reduces to sequentially solving the Nash Equilibria of normal form games along the state space.

Finally, our paper contributes to the empirical literature on electricity markets. Most of the literature has focused on firms exercising market power through strategic bidding and withholding of existing capacity—see Green and Newbery (1992) and Wolfram (1998) for early contributions, and more recently, Borenstein et al. (2002), Hortacsu and Puller (2008), Mansur (2007), and Bushnell et al. (2008). In contrast to these papers, we model strategic investment in new capacity, which has only received limited attention (e.g. Bushnell and Ishii (2007)).

[8] Recent papers in this literature include Fowlie (2010) on the interaction of the NO_x Budget Program with rate-of-return regulation, Cicala (2015) and Abito (2019a) on the interaction between the Acid Rain Program and agency problems, Davis and Muehlegger (2010) on U.S. natural gas distribution, Hausman and Muehlenbachs (2016) on methane leaks, Ryan (2012) on industry concentration and the Clean Air Act Ammendments, and finally Fowlie et al. (2016) on the interaction of market power, industry dynamics and market-based mechanisms to limit CO_2 emissions.

[9] Chen et al. (2009) compute the MPNE in their game with network effects by solving a two-stage subgame of compatibility and pricing at each given state. Doraszelski and Escobar (2010) characterize an MPNE as the NE of normal form games (one for each state) to apply an analogous purification argument as Harsanyi (1973). Abito et al. (2019) use a similar trick to construct bounds in the context of supergames that allow for states.

Structure of the Paper

The remainder of the paper is organized as follows. Section 2 gives some background on our empirical setting. We present our empirical model in Section 3, followed by a discussion of estimation and empirical results in Section 4. Section 5 contains our counterfactual analysis and we finally conclude in Section 6. An Online Appendix contains the details on data construction, estimation procedure, and computational approach for the counterfactuals.

2 Background

2.1 PJM Electricity Market

The Pennsylvania-New Jersey-Maryland (PJM) Interconnection operates the world's largest wholesale electricity market as the regional transmission organization for all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia (Figure 2). PJM coordinates the buying, selling and delivery of wholesale electricity through its Energy Market which began operations in 1997. As the market operator, PJM balances the needs of buyers, sellers and other market participants and monitors market activities to ensure "open, fair and equitable access."[10] To give the reader an idea of the transactions in PJM, between 2003 and 2012, the value of transactions in PJM's real-time energy market grew from approximately \$13 billion to \$26 billion (Table A5). Total billings in 2012 were close to \$29 billion.

Table 1 shows installed capacity by source using data from the PJM State-of-the-Market (SOM) reports for 2005-2012.[11] Total capacity increased from 163,500 MW in 2005 to 182,000 in 2012, with a compound annual growth rate (CAGR) of 1.8%. During the same time, coal-fired capacity increased from 67,000 MW to 76,000 MW, while gas-fired capacity increased from 44,000 to 52,000 with implied CAGRs of 1.93% and 2.47%, respectively. Averaged across years, the two fuels combined account for 70% of the total capacity, with coal accounting for 40% and gas accounting for the remaining 30%. Nuclear's share of total capacity is 18.5% while that for oil is 6.5%. The remaining sources—hydro, wind, and solid waste— account for the remaining 5% of total capacity.

Ownership of coal and natural gas capacity in each participating state are highly concentrated. For example, in 2012, all coal capacity in Kentucky is owned by a single company

[10]See http://www.pjm.com/~/media/about-pjm/newsroom/fact-sheets/pjms-markets-fact-sheet.ashx. As of December 31, 2012, PJM had installed generating capacity of about 182,000 megawatts (MW) and a peak load close to 154,000 MW. See Table 1-1 in Volume 1 of the State-of-the-Market report for 2013.

[11]See http://www.monitoringanalytics.com/reports/PJM_State_of_the_Market/2016.shtml.

(AEP), while all natural gas capacity in North Carolina is owned by Dominion. The HHI for capacity in states that have at least two companies ranges from 2,209 (Pennsylvania) to 9,876 (Indiana) for coal, and from 1,786 (Pennsylvania) to 9,910 (Kentucky) for natural gas.

2.2 CO_2 Emissions Regulation

The closest that the U.S. has come to regulating CO_2 emissions was through the Clean Power Plan (CPP) formulated during the Obama Administration to limit CO_2 emissions from fossil-fired power plants. Fossil fuel-fired plants, which are mostly coal- and gas-fired, are one of the largest single source of CO_2 emissions, accounting for about a third of U.S. total greenhouse gas emissions. The CPP called for a 32% reduction in CO_2 emissions from the power sector by 2030 relative to its 2005 levels. Although the Trump Administration proposed to repeal (October 7, 2018) and replace (August 21, 2018) the Obama-era rules,[12] the CPP still provides a useful example of what CO_2 emissions regulation can look like since future regulations will still be based on the same legal framework, the Clean Air Act (CAA).

Using the authority given by the CAA, the U.S. Environmental Protection Agency (EPA) finalized two sets of rules aimed to address CO_2 emissions from fossil-fired power plants (EPA (2015)). In this paper, we collectively refer to the two sets of rules as the CPP, though technically the CPP refers to the set of emission targets applied to *existing* plants (Section 111(d) of the Clean Air Act) while the rules that are applicable to *new* sources are part of the "Carbon Pollution Standard for New Plants" (Section 111(b)).

Section 111(b) gives the EPA authority to set standards or emissions limitations on new, modified, or reconstructed plants.[13] Even though the EPA cannot require a specific technology that firms should adopt under Section 111(b), the emission limits set by the EPA in the case of the CPP essentially precluded technologies that would not meet the limit. For example, the final CPP rule specified a limit of 1,000 lbs of CO_2 per MWh for gas-fired plants, which was feasible only for the latest combined-cycle technology. For coal-fired plants, the limit was 1,400 lbs of CO_2 per MWh, which was achievable only with carbon capture and storage technology, a technology that is costly and not widely available.

Under Section 111(d), the CPP established interim and final rate-based (lbs./MWh) and mass-based (short tons) state goals regarding CO_2 emissions. The interim goals were for the period 2022–2029, while the final goals were for 2030. The EPA gave the states the

[12] The CPP has since been replaced by the Affordable Clean Energy rule, which largely leaves states to decide whether and how to regulate CO_2 emissions.

[13] Units that are built, modified or reconstructed after the prevailing Section 111(d) targets were set are, by statute, classified as "new" as long as the same targets are in place. For example, in the original CPP, the targets were expected to remain at least until 2030. Only when targets are revised will these sources be reclassified as existing.

flexibility to develop and implement plans to ensure that power plants in their state—either individually, together, or in combination with other measures—were capable to achieve the interim and final goals.

To set these targets, the EPA determined the best system of emission reductions (BSER) that had been demonstrated for a particular pollutant and particular group of sources by examining technologies and measures previously used. The BSER consisted of three building blocks: (i) reducing the carbon intensity of electricity generation by improving the heat rate of existing coal-fired power plants, (ii) substituting existing gas-fired generation for coal-fired generation, and (iii) substituting generation from new renewable sources for existing coal-fired generation.[14]

Table 2 shows the CPP mass-based targets for the eleven PJM states used in our empirical analysis, noting that the targets have been adjusted to account for the fact that only a part of the plants located in Illinois, Indiana, Kentucky, and North Carolina fall under the PJM footprint. The first observation regarding the information in this table is the gradual reduction in total emissions (short tons) for all states between the first and final years of CPP. The second observation is the notable heterogeneity in targets across states. For example, in the first year of CPP, the target for Maryland is 18.2 million short tons, while its counterparts for Ohio and Pennsylvania are 92.1 and 110.2, respectively. This difference in CO_2 emissions reflects the difference in generation from coal, gas, and oil, for the three states in 2012. This "baseline" generation is a key component in the calculation of the targets (Table 3).

The stringency of the target varies substantially across states and this variation is the source of gains from trade from coordinating separate CO_2 markets. Taking 2012 CO_2 emissions as a base, the targets require a reduction of 50% or more in Kentucky (52%), Illinois (52%), Indiana (50%), West Virginia (50%) and Maryland (50%). On the other hand, the targets require a reduction smaller than 50% in Ohio (49%), Pennsylvania (46%), North Carolina (39%), Virginia (30%) and New Jersey (24%). Given the variation in the stringency of the targets, it is interesting to note the distribution of the coal- and gas-fired capacity for some of the dominant firms in the region as this would influence how a firm would reallocate its generation. For example, the fraction of the combined (coal- plus gas-fired capacity) in a state that requires less than 50% CO_2 emissions reduction is as follows: First Energy (52%), AEP (39%), Dominion (75%), and Duke (89%).

[14]EPA applied the building blocks to all coal and natural gas units in the three major electricity interconnections in the country (Eastern, Western, and ERCOT (Texas)) to produce regional emission rates. From the resulting regional rates for coal and natural gas units, EPA chose the most readily achievable rate for each category to arrive at the CO_2 emission performance rates for the country that represent the BSER. The same CO_2 emission performance rates were then applied to all affected sources in each state to arrive at individual statewide rate-based and mass-based goals. Each state had a different goal based upon its own particular mix of different sources.

We end this section with a remark. The separate rules for existing and new plants provide two useful modeling shortcuts. First, because only emissions from existing plants are counted against the state-level CO_2 targets, the location of a new plant is irrelevant with respect to the CO_2 price. Location choice for new capacity is an interesting but extremely complicated problem, especially in our case, where multiple CO_2 markets and the electricity market all have to clear simultaneously in each period. Second, since firms must essentially invest in plants that have the best available technology (BAT), new plants will have the property of being infra-marginal which, as we show in the section, helps us reduce the size of the state space.

3 Model

We now present our model of the PJM wholesale electricity market. Figure 3 provides an overview of the timing of the model. We model the market interaction as a dynamic stochastic game where firms first decide on whether to invest in new plants, and then given their current portfolio of plants, they compete to supply electricity. Each firm owns a portfolio of plants that can differ in fuel-type, capacity, efficiency, emissions rate, and location. Investment and supply decisions determine the portfolio of plants and the share of electricity output for each fuel type, which, in turn, determine the level and location of CO_2 emissions.

We distinguish between two groups of firms in our model. There is a group of N *strategic* firms, where N is much smaller than the total number of firms. We assume that only strategic firms can invest in new plants. We treat the rest of the firms as a *fringe*. The fringe is exogenously endowed with a portfolio of plants that remains fixed throughout the analysis.

In what follows, we first describe how we model electricity demand and firms' supply decisions conditional on the portfolio of plants. We then discuss how plant portfolios endogenously evolve through a firm's choice of investment. We close the section with a discussion of equilibrium.

3.1 Electricity Demand

To model demand, we adapt the approach in Bushnell et al. (2008) (henceforth, BMS) using monthly data and a more parsimonious specification. The need for parsimony stems from the fact that we only have 120 monthly observations for 2003–2012, whereas BMS uses roughly 3,000 hourly observations. We use fringe supply to refer to the supply subtracted from the vertical inelastic market demand to obtain the residual demand for the strategic firms, which we assume to be the firms listed in Table 4. This fringe supply consists of the following: (i) net imports, (ii) supply of fringe firms, and (iii) supply of strategic firms from sources other than coal and gas. We then estimate the following fringe supply function:

$$\begin{aligned} q_\tau^{fringe} &= \sum_{m=1}^{12} \alpha_m d_{m\tau} + \sum_{y=2}^{10} \alpha_y d_{y\tau} + \beta ln(p_\tau^w) + \mu_1 CDD_\tau + \mu_2 CDD_\tau^2 \\ &+ \mu_3 HDD_\tau + \mu_4 HDD_\tau^2 + \varepsilon_\tau, \end{aligned} \tag{1}$$

where $d_{m\tau}$ and $d_{y\tau}$ are the fixed effects for month m and year y, respectively. Additionally, p_τ^w is the average monthly real-time system-wide locational marginal price in the PJM wholesale electricity market. We proxy for electricity prices in the states surrounding PJM using average cooling (CDD_τ) and heating (HDD_τ) degree days and their squares accounting for the fact that the PJM footprint expanded during the period in our sample. Finally, ε_τ is the idiosyncratic shock. We introduce some compact notation writing (1) as follows:

$$\widehat{q}_\tau^{fringe} = \widehat{\lambda}_\tau + \widehat{\beta} ln(p_\tau^w) \tag{2}$$

$$\widehat{\lambda}_\tau \equiv \sum_{m=1}^{12} \widehat{\alpha}_m d_{m\tau} + \sum_{y=2}^{10} \widehat{\alpha}_y d_{y\tau} + \widehat{\mu}_1 CDD_\tau + \widehat{\mu}_2 CDD_\tau^2 + \widehat{\mu}_3 HDD_\tau + \widehat{\mu}_4 HDD_\tau^2. \tag{3}$$

The residual demand Q_τ^S for the strategic players is then given by:

$$Q_\tau^S = Q_\tau - \widehat{q}_\tau^{fringe} = Q_\tau - \widehat{\lambda}_\tau - \widehat{\beta} ln(p_\tau^w) \tag{4}$$

Finally, we write:

$$Q_\tau^S = \widehat{a}_\tau - \beta ln(p_\tau^w), \quad \widehat{a}_\tau \equiv Q_\tau - \widehat{\lambda}_\tau. \tag{5}$$

Seasonality and Peak Periods. Our framework allows for shifts in demand to accommodate both seasonality (cross-month variation) and peak periods (within-day variation). Both sources of fluctuations in demand are important for a realistic representation of electricity wholesale markets and are introduced in the model through shifts in the intercept of the residual demand curve. Using τ to denote the demand curve in year y and month m, and letting peak period be $p \in \{off, peak\}$, the following holds:

$$a_\tau^{off} = a_y + a_m \tag{6}$$
$$a_\tau^{peak} = (a_y + a_m)a^{peak} \tag{7}$$

where a_y is the baseline yearly intercept in the demand curve, and a_m and $a^{peak} > 1$ are, respectively, the seasonality and peak period shifters.

We estimate and solve the model separately for each pair of m and p. Whenever we report monthly figures they are averages over all the different prices obtained through that month, weighted by the fraction of hours that demand is either peak or off-peak.

3.2 Firms

3.2.1 Generation Cost

Following BMS and Mansur (2007), the marginal cost of generating electricity ($/MWh) for plant i at time t is given by:

$$c_{it} = VOM_{it} + HR_{it} \times \left(P_t^f + P_t^s r_{it}^s + P_t^n r_{it}^n \right), \tag{8}$$

where VOM is the variable non-fuel operations-and-maintenance cost ($/MWh), and HR is the heat rate (MMBtu/MWh) that captures efficiency in turning heat input from fuel to electricity. Additionally, r^s and r^n are the fuel-specific SO_2 and NO_x emission rates (lbs./MMBtu), when applicable. Finally, P^f is the fuel price ($/MMBtu) while P^s and P^n are the SO_2 and seasonal NO_x permit prices ($/lb.). In our empirical analysis, the VOM costs, the heat rates, and the emission rates, exhibit variation by plant and year. The fuel prices exhibit variation by firm, year, and month. The permit prices exhibit variation by year and month.

A firm's marginal cost function is a step function where each step represents a plant with capacity K and marginal cost c. It is constructed by ordering its plants in terms of their marginal costs. Because we observe all of the components in (8), we can compute each firm's marginal cost directly from the data.

3.2.2 Evolution of Plant Portfolios

Investment affects the shape of the marginal cost function by changing the firm's portfolio of plants. In the beginning of each year, firms choose to invest in coal- or gas-fired capacity. Although we do not assume a minimum size of a plant that firms can invest in, we assume that firms can choose the capacity of the new plant in increments of 1 megawatt (MW). To determine the heat rate of new plants, we rely on Section 111(b) of the Clean Air Act discussed in Section 2.2, which essentially requires that new capacity is of the best available technology (BAT). To implement this assumption in our model, we assume that firms invest in plants that have the best (lowest) heat rate during the investment year.

Aside from simplifying the choice of the plant type firms invest in, the BAT assumption also help us reduce the dimensionality problem of our model, which emerges due to two reasons. First, we need to take stock of the type of plant firms invest in at each point in time. Second, when evaluating different investment strategies, firms have to be able to compute future profit flows under different investment scenarios involving different paths for their plant portfolio.

Figure 4 illustrates how the BAT assumption helps us to address the dimensionality problem. Since new plants must have the best heat rate, they are likely to be infra-marginal, at least, in the time horizon whereby plants that existed in 2013 are still supplying positive quantities in equilibrium. The two lowest steps of the supply curve in panel (a) of Figure 4 represent investment in new capacity, while the remaining portion of the supply curve corresponds to existing capacity.[15] Panel (a) illustrates the market equilibrium when we keep track of all the information about new capacity that the firm invests in. Panel (b) instead combines the two lowest steps into one. As one can see, it suffices to keep track of an average of all the new capacity that the firm invests in because averaging across these individual units does not affect the equilibrium quantities, prices, and profits. Thus, as long as new capacity is infra-marginal, tracking the firm-level cumulative BAT capacity and the associated weighted average heat rate is sufficient for our empirical analysis.

Denoting fuel-type as $f \in \mathscr{F} = \{coal, gas\}$, let i^f_{jt} be the investment by firm j in coal- or gas-fired capacity at time t. In addition, let $\underline{K}_{jt}$ be the cumulative BAT capacity given by:

$$\underline{K}_{jt+1} = \underline{K}_{jt} + i^{coal}_{jt} + i^{gas}_{jt}. \tag{9}$$

Because the heat and emission rates for coal- and gas-fired capacity are different, we keep track of the share of gas-fired BAT capacity:

$$\underline{S}_{jt+1} = \frac{\underline{S}_{jt}\underline{K}_{jt} + i^{gas}_{jt}}{\underline{K}_{jt+1}}. \tag{10}$$

For heat rates, as well as the remaining components of the fuel-specific marginal costs, we

[15]It is not necessary for new capacity to represent the cheapest plants in the supply curve since equilibrium quantities, prices and profits are invariant to rearranging the “infra-marginal” steps of the supply curve.

track a weighted average at time t. For example, in the case of the heat rate for gas-fired BAT capacity, we track the following weighted average:

$$\underline{HR}^{gas}_{jt+1} = \frac{\underline{S}_{jt}\underline{K}_{jt}}{\underline{S}_{jt}\underline{K}_{jt} + i^{gas}_{jt}}\underline{HR}^{gas}_{jt} + \frac{i^{gas}_{jt}}{\underline{S}_{jt}\underline{K}_{jt} + i^{gas}_{jt}} hr^{gas}_{jt}, \tag{11}$$

where hr^{gas}_{jt} is the heat rate associated with new investment in gas-fired capacity. The BAT capacity for firm j at time t is $\underline{K}_{jt}$ and the marginal cost is given by:

$$\underline{c}_{jt} = (1 - \underline{S}_{jt})\underline{c}^{coal}_{jt} + \underline{S}_{jt}\underline{c}^{ng}_{jt}, \tag{12}$$

where $\underline{c}_{jt}$ is computed using (8) noting that there are fuel-specific components entering the equation.

Holding the vector of prices constant, a firm's new marginal cost curve, which is a collection of (K_{jt+1}, c_{jt+1}) points, is obtained through a shift of the marginal cost curve at time t (see Figure 5). For example, suppose there is only one firm investing in gas-fired capacity that gives rise to BAT capacity $\underline{K}_{jt}$ and marginal cost $\underline{c}_{jt}$, which we assume is less than the marginal cost of all existing capacity for illustration purposes. The leftmost point of the new marginal cost curve becomes $(\underline{K}_{jt}, \underline{c}_{jt})$. The remaining points of the marginal cost curve become $(K_{-jt} + i^{gas}_{jt}, c_{-jt})$, which is consistent with a horizontal shift equal to the amount of investment.

Renewable Sources. When making investment decisions, firms take into account the expected evolution of generation capacity from renewable sources. Our model accommodates changes in capacity due to renewable sources in a flexible way through exogenous shifts in the BAT capacity over time. We do not, however, allow investment in renewable sources to respond strategically to changes in the coal- and gas-fired capacity. This assumption is supported by binding Renewable Portfolio Standards (RPSs) we observe in the data, at least, in the medium run. An RPS mandates that a specific fraction of all electricity generated has to come from renewable sources. With a binding RPS, investment in renewable sources is driven by regulation rather than profit maximization. We collect information on the RPS future mandates for the different states that comprise the PJM market and use these in our simulations.

3.3 Equilibrium

3.3.1 Electricity Market Equilibrium

To model firms' supply decisions in the wholesale electricity market, we build on the results in Wolak (2000) and BMS. Wolak and BMS show that electricity markets in the presence of forward contracts, as is the case for PJM, generate outcomes that are much closer to perfect competition than to an oligopoly (Cournot) game.[16] Therefore, we implement our model as if firms were price-takers producing electricity subject to capacity constraints.[17] The equilibrium wholesale electricity price is then determined by the intersection of the demand and supply curves.

Market supply is determined by ordering all available capacity in terms of its marginal costs, similar to Figure 5. This "merit order" dictates the sequence in which the various plants are dispatched as the demand for electricity increases. The equilibrium wholesale price is the marginal cost of the most expensive plant called to serve demand. Given fuel and emissions permit prices, the market supply function is a step function described by the pair (K, c), where K is the capacity with marginal cost less than or equal to c. Given that we observe all of the components in (8), we can construct this step function directly from the data.

Remark. In our model, investment decisions are strategic. Hence, firms decide on investment considering its impact on other firms, and vice-versa. The assumption of a perfectly competitive wholesale market combined with strategic investment, under the existence of forward commitments, is not inconsistent with theory. For example, Adilov (2012) models firms' investment in capacity in order to study the effects of forward markets on competition and efficiency extending the standard Allaz and Villa (1993) framework. The forward market takes place after the investment decisions are committed but before the spot market. Importantly, endogenous capacity choices affect strategic behavior in the forward and spot markets. Outside of electricity market settings, Dixon (1985) analyzes a model where the

[16] We confirmed the results from BMS in our own setting by modeling the wholesale electricity market assuming perfect competition and Cournot. We found that perfect competition generates equilibrium prices that are reasonable and consistent with predictions from futures markets, while Cournot produces equilibrium prices that are unrealistically much higher. In our case, forward commitments are not as straightforward to deal with as in BMS since our model is dynamic. Either we assume forward commitments are exogenous and determine its evolution outside of the model (or simply take them as fixed), or treat these as endogenous and model how firms' choose these commitments in equilibrium. While interesting, modeling the endogenous evolution of forward commitments is beyond the scope of the paper.

[17] Our assumption for a competitive setting in the PJM energy market is also consistent with the conclusions in the State-of-the-Market (SOM) reports prepared by the PJM Market Monitoring Unit for 2003–2012. The SOM reports analyze competition within, and efficiency of the PJM markets using various metrics, such as market concentration, the residual supply index, and price-cost markups.

market is competitive but firms can strategically invest. He finds that, in equilibrium, firms under-invest to drive prices above "potential" marginal cost, i.e. what marginal cost would have been if the firm invested the socially optimal level.

3.3.2 Markov Perfect Nash Equilibrium

The actions chosen by each firm j are represented by $a_{jt} = \{q_{jt}, i^{coal}_{jt}, i^{gas}_{jt}\}$ and let $\mathbf{a}_t$ be the vector of firm actions at time t. The variable q_{jt} captures the output of firm j's plants, while i^f_{jt} is investment as defined earlier. Although we use a single time subscript to maintain notational simplicity, the output decisions in the electricity market are monthly, while the investment decisions are annual.

The state vector is given by:

$$\mathbf{s}_t = \left(\alpha_t, \mathbf{p}^F_t, \{\underline{K}_{jt}, \underline{S}_{jt}, \underline{HR}^{coal}_{jt}, \underline{HR}^{ng}_{jt}\}^N_{j=1}\right). \tag{13}$$

The endogenous part of the state vector, $\{\underline{K}_{jt}, \underline{S}_{jt}, \underline{HR}^{coal}_{jt}, \underline{HR}^{ng}_{jt}\}$, relates to BAT capacity investment and its evolution is discussed in the previous section. In terms of the exogenous state variables, α_t is the intercept of the inverse residual monthly demand for electricity and $\mathbf{p}^f_t$ is a vector of monthly coal and gas prices.[18] The future path of the exogenous state vector is allowed to exhibit some uncertainty, which can affect the investment decisions.

We write the static profit function as follows:

$$\pi_{jt}(\mathbf{a}_t, \mathbf{s}_t, \nu_{jt}) = \overline{\pi}_{jt}(\mathbf{a}_t, \mathbf{s}_t) - \Gamma_{jt}(\mathbf{a}_t, \nu_{jt}), \tag{14}$$

where

$$\overline{\pi}_{jt}(\mathbf{a}_t, \mathbf{s}_t) \equiv p^r_{jt} \times q^r_{jt} + p^w_t \times (q_{jt} - q^r_{jt}) - C(q_{jt}, \mathbf{s}_t) \tag{15}$$

represents the profit from the wholesale electricity market excluding the investment cost $\Gamma_{jt}(\mathbf{a}_t, \nu_{jt})$. Here, p^r_{jt} is the price the firm receives from retail sales commitments q^r_{jt}, which are assumed to be sunk at the time production decisions are made for the wholesale market, and p^w_t is the equilibrium wholesale electricity price. Finally, $C(q_{jt}, \mathbf{s}_t)$ is the total cost of producing q_{jt} given $\mathbf{s}_t$.

[18] The vector of monthly SO_2 and seasonal NO_x permit prices is set at zero, consistent with the current situation in the electric power industry. Therefore, they are not included in the state vector. Likewise, the remaining components of the BAT cost, such as the VOM cost, are held constant at the current values and, hence, need not be considered in the state vector.

Investment cost is given by:

$$\Gamma_{jt}(\mathbf{a}_t, \nu_{jt}) = \sum_{f \in \mathscr{F}} (\gamma^f + \nu^f_{jt}) i^f_{jt}, \tag{16}$$

where ν_{jt} is a private shock that is independently distributed across firms and time and drawn from a common distribution, and γ^f is an investment parameter that we need to estimate.[19]

Firms' strategies depend only on the current state (including the private investment shock) as in Ericson and Pakes (1995). That is, for firm j, strategy σ_j maps the state and private shock into actions. The strategy profile $\boldsymbol{\sigma}$ is a Markov Perfect Nash Equilibrium (MPNE) if each firm j's strategy σ_j generates the highest value among all alternative Markov strategies σ^l_j given the rivals' profile $\boldsymbol{\sigma}_{-j}$:

$$V_j(\mathbf{s}; \boldsymbol{\sigma}) \geq V_j(\mathbf{s}; \sigma^l_j, \boldsymbol{\sigma}_{-j}), \tag{17}$$

where $V_j(\mathbf{s}; \boldsymbol{\sigma})$ is the ex ante—before observing the realization of the private shocks—value function for firm j given by

$$V_j(\mathbf{s}; \boldsymbol{\sigma}) = \sum_{t=0}^{\infty} \beta^t E\left[\pi_{jt}(\mathbf{a}_t, \mathbf{s}_t, \nu_{jt}) | \mathbf{s}_0\right] \tag{18}$$

amd β is the discount factor common to all firms.

Remark. In our model, the benefits from investment come from the profits firms earn in the wholesale electricity market. However, PJM encourages investment in new capacity through capacity auctions. The motivation for the capacity auctions is adequacy of resources to ensure that the demand for electricity can be met at all times in the near future. Utilities and other electricity suppliers, collectively known as load serving entities (LSEs), are required to have the resources to meet their customers' demand plus a reserve. The LSEs can meet the resource requirement with generating capacity they own, with capacity they purchase from others under contract, through demand response—in which customers reduce their usage in exchange for payment—or with capacity obtained through the capacity auctions themselves.

Since we do not model capacity auctions, the reader may worry that our setup fails to account for capacity payments that incentivize firms to invest. Although we do not explic-

[19]The specification for investment cost given in (16) only allows for *positive* adjustments to capacity. A version of (16) with scrap value would be $\Gamma_{jt} = \sum_f 1_{[i^f_{jt}>0]}(\gamma^f_1 + \nu^f_{1jt}) i^f_{jt} + 1_{[i^f_{jt}<0]}(\gamma^f_2 + \nu^f_{2jt}) i^f_{jt}$ as in Ryan (2012). Thus, unlike Ryan (2012) or Fowlie et al. (2016), there is no scrap value from closing down a plant. Given that we do not have fixed costs in our model, the firm will just keep unused plants idle.

itly model capacity payments, our model can accommodate such payments. With capacity payments, Γ_{jt} becomes the investment cost *net of* their expected future value. Of course, this interpretation is valid only when all new investment receives capacity payments. Furthermore, our model can accommodate heterogeneity in capacity payments because of zonal (location-specific) pricing through the private shock ν_{jt}. It is also important to note that during the period relevant for our analysis (2003–2012), capacity payments have accounted for 6% of the total wholesale price per MWh when energy payments accounted for 82%.[20]

4 Estimation

The key components of the structural model that we need to estimate are generation costs, the fringe supply curves, and the investment cost parameter. We compute plant-level generation costs directly from the data, as described in Section 3.2.1. We estimate fringe supply using two-stage least squares where monthly quantity demanded serves as our instrument for price, exploting the idea that short-run wholesale electricity demand is completely inelastic. Finally, we estimate the investment cost parameter using the two-stage methodology in Bajari et al. (2007). In the first stage, we estimate policy functions from the data using observable state variables. The policy functions are reduced-form because they provide estimates of parameters that are not primitives of the underlying economic model of investment. In the second stage, we search for the investment cost parameter that best rationalizes firms' observed behavior and transitions of the state variables. The advantage of this approach is that the investment cost parameter can be estimated without the need to solve for the equilibrium of the game. Section A.4 in the Online Appendix discusses estimation in greater detail. We now present our results.

[20]See Table 9 of the 2012 PJM State of the Market Report Volume I. Modeling firm behavior in the capacity market is beyond the scope of the paper. As a background, effective June 2007, the PJM Capacity Credit Market (CCM), which had been the market design since 1999, was replaced with the Reliability Pricing Model (RPM) capacity Market. Under the CCM, LSEs could acquire capacity resources by relying on the PJM capacity market, by constructing generation, or by entering into bilateral agreements. Under RPM, there is a must-offer requirement for existing generation that qualifies as a capacity resource and a mandatory participation for LSEs with some exceptions. LSEs must pay the locational capacity price for their zone and zonal prices may differ depending on transmission constraints. LSEs can own capacity or purchase capacity bilaterally and can offer capacity into the RPM auctions when no longer needed to serve load. Capacity obligations are annual and Base Residual Auctions (BRAs) are held for delivery years that are three years in the future. There are also incremental auctions that may be held for each delivery year if there is a need to procure additional capacity resulting from a delay in a planned large transmission upgrade that was modeled in the BRA for the relevant delivery year. Bushnell et al. (2017a) provide an in-depth discussion of the capacity markets.

4.1 Estimation Results

Fringe Supply Estimates. Table 5 contains the estimates for the fringe supply equation.[21] The price coefficient, which is of main interest for the subsequent analysis, is generally highly significant. According to our preferred specification, in which the price enters in logs, the implied elasticity at the sample averages of fringe supply and price of is 0.74.

Investment Cost Estimates. The estimate of investment cost reported in Table 7 is in \$/MW of gas-fired capacity. Note that given the lack of investment in coal-fired capacity implied by our model, it is not possible to estimate the costs for coal-fired capacity. Our estimate of around \$1.4 million per MW for gas-fired capacity is comparable to the estimates in Spees et al. (2011), which are up to \$1 million per MW. The reported standard error of approximately \$32,000 per MW does not take into account the first-stage estimation error.[22]

4.2 Time Paths and Model Fit

Exogenous State Variables. Figure 6 shows the time series paths (2013-2062) for various exogenous state variables in the model. We start by showing the path for the annual average of the residual demand intercept $\widehat{a}_t$ (panel (a)). We take the value of the intercept from 2012 from the estimated residual demand curve, and let it increase at a rate of 1% per year from that point onwards. We allow the monthly demand curve to exhibit seasonality patterns consistent with the data. We do this by regressing demand (load) on month dummies and saving the corresponding estimated coefficients, which are then used to adjust the corresponding monthly demand intercept around the annual average. Moreover, for each month, there are two different demand curves: one for peak and another for off-peak periods. When we simulate our model forward, we assume that the relation between these two demand curves (given by parameter a^{peak} in (7)) stays constant over time, and equivalent to historical averages.

The coal heat rates associated with new investment are assumed to be fixed at their 2012 levels (10 MMBtu/MW), while their gas counterparts are assumed to be falling over time from 7.6 MMBtu/MWh to 7.2 MMBtu/MWh; see panel (b). The trend for the gas heat rates associated with new investment is obtained by projecting the linear trend of the log gas BAT heat rates for 2003–2012 to 2013–2062. The remaining cost components, VOM costs and CO_2 rates, are held constant from 2013 onwards.[23]

[21] We refer the reader to Section A.2 for some additional descriptive statistics.

[22] We calculate standard errors using 1,000 bootstrap replications by resampling from the moment inequalities and ignoring the first-stage estimation error as in Bajari et al. (2013).

[23] The CO_2 emission rates are relevant in the policy evaluations section of the paper. The SO_2 and NO_x

In the case of coal prices, we extrapolate the EIA annual projections for 2013–2035 from the 2012 Annual Energy Outlook reference case to 2062 using the implied compound annual growth rate (panel (c)). For gas prices, we use monthly NYMEX Henry Hub futures prices for 2013–2028. We expand the series until 2062 using flat extrapolation of the 2008 levels. Given the collapse in SO_2 and seasonal NO_x permit prices in recent years, we assume that they will remain at zero for 2013–2062.[24]

Endogenous Variables. Figure 8 shows similar time paths for a variety of endogenous variables, such as market-wide outcomes, and firm-level generation, profits, capacity, and heat rates. The BAT capacity, which is exclusively gas-fired, exhibits an upward trend increasing from 1,400 MW in 2014, the first year of investment, to 10,900 MW in 2062 (panel (a)). As a result, the share of output (electricity generation) that BAT capacity accounts for increases over time with roughly half of the increase taking place the first 15 years (panel (b)). Electricity generation (panel (c)) and prices (panel (d)) increase over time, too. Following a period with a downward trend between 2013 and 2030, the share of gas in electricity generation increases from 18% to 30% (panel (e)). After about 20 years of growth of the share of coal in electricity generation that peaks at 40%, we see slight a decline in the later years. The share of sources other than coal and gas in electricity generation decreases from 47% in 2013 to 31% in 2062 (panel (f)); recall that we assume no investment in these fringe sources.

Table 8 shows the investments in gas-fired capacity by firm for 2013–2062. During the same period, there is no investment in coal-fired capacity. Overall, we see 51 instances of investment associated with close to 11,000 MW of gas-fired capacity. Three firms account for roughly 3/4 of the total investment. Exelon accounts for 2,400 MW, followed by NRG with around 2,550 MW and AES with 2,400 MW. Exelon invests 15 times. AES and NRG invest 12 times. It is important to keep in mind that this table tracks investment flow and not net investment. Investment may imply replacement of old units that become more costly to operate with new units. A detailed timeline of investment by firm is available in Figure 7.

Model Predictions. Finally, in Figure 9 we compare the electricity price implied by our model with the on-peak electricity price for PJM from NYMEX futures for the period 2016/04–2019/12.[25] As we can see, our model tracks reasonably well the NYMEX futures

emission rates do not impact our calculation since the price of the corresponding permits price is set to zero in the forward simulations.

[24] Our use of Henry Hub futures prices for gas and the assumption regarding zero permit prices are both consistent with the approach taken in PJM (2016) regarding projections of gas and permit prices.

[25] Off-peak is a period of time when consumers typically use less electricity: normally, weekends, holidays or times of the day when many businesses are not operating. PJM typically considers New Year's Day,

prices.[26]

5 Counterfactual Simulations

We use the estimated model to compare economic outcomes under counterfactual CO_2 emissions regulations. Specifically, we simulate the model under two regulatory regimes: plants face a PJM-wide regional CO_2 market and plants face uncoordinated state-by-state markets. Our goal is to measure the inefficiency with state-by-state CO_2 markets relative to the regional one. We begin our analysis by looking at the "static" case, where we compute outcomes holding best available technology (BAT) capacity fixed. In this case, investment is exogenous and BAT capacity is the same in the two regulatory regimes. We then shift our focus to the "dynamic" case, where investment is the result of firms' optimal behavior and BAT capacity is endogenous. Different investment incentives now impact the comparison in economic outcomes between the two regulatory regimes. We provide a detailed discussion of computation in Section A.5 of the Online Appendix.

To implement the counterfactual regulatory regimes, we assume that the PJM states are subject to the mass-based targets of the Clean Power Plan (CPP) shown in Table 2. These targets limit the quantity of CO_2 emissions (in short tons) that states can emit annually. There are interim targets for 2022—2029 followed by a permanent target from 2030 onwards. With separate CO_2 markets, each state's emissions have to be less than or equal to the annual targets. With a single CO_2 market, emissions only need to be less than or equal the sum of the targets across the PJM states (see Figure 10). Although we do not explicitly model a market for emissions permits, we take the shadow prices of the CO_2 emissions constraints as our CO_2 prices. In the case of the single CO_2 market, there is one CO_2 price corresponding to the shadow price of the regional emissions constraint. In the case of separate CO_2 markets, the CO_2 prices are state-specific and correspond to the shadow price of each state's emissions constraint.

The CO_2 price increases the cost of generating electricity each plant. This additional cost is different for plants with different heat (MMBtu/MWh) and emission (lbs./MMBtu)

Memorial Day, Independence Day, Labor Day, Thanksgiving Day and Christmas Day, as well as weekend hours and weekdays from 11 p.m. to 7 a.m. as off-peak. See `http://www.pjm.com/en/Glossary`.

[26]In Figure A3, we compare the behavior of heat rates, fuel prices, generation and capacity before and after 2012, the last year in our sample. In general, we see a transition that is smooth and a trend towards more gas in both generation and capacity. We do not allow for explicit divestitures but some of the coal capacity will start to become extra-marginal.

rates, and locations. The marginal cost for plant i in state s at time t is thus given by

$$c^C_{ist} = c_{ist} + P^C_{st} \times r^C_{ist} \times \zeta, \tag{19}$$

where c_{ist} is the generation cost excluding the cost of emissions (\$/MWh), P^C_{st} is the CO_2 price (\$/ton), r^C_{ist} is the heat rate-adjusted emissions rate (lbs./MMBtu $\times$ MMBtu/MWh), and ζ is an appropriate scaling factor to take into account units of measurement. In the case of a single market, $P^C_{st} = P^C_t$, $\forall s \in S$, where S is the set of the eleven PJM states listed in Table 2.

Since CO_2 prices affect plants' generation cost, these prices also affect the shape of the wholesale electricity market supply curve. Market demand and supply determine each plant's equilibrium electricity generation, which in turn determine emissions. Emissions then determine the extent the emissions constraint binds and the resulting equilibrium CO_2 price. Therefore, equilibrium in each period requires finding a set of prices that simultaneous clear the electricity and emissions markets.

We make a series of assumptions for computational feasibility, but are, nonetheless, consistent with the institutional details of our setting. First, only emissions from existing capacity built by 2012 are subject to CO_2 prices. Although emissions from capacity built after 2012 are exempt from the CO_2 price, post-2012 capacity must have the lowest heat and emissions rate during the investment year. Second, we assume that heat rate improvements are exogenous.[27] Third, generation from renewable sources increases exogenously according to annual growth rates in the CPP.[28] Finally, we assume an upper bound of \$100 for the CO_2 price and set the post-2030 CPP targets at their 2030 levels.[29]

5.1 Static Analysis: Exogenous Investment

Holding capacity fixed, electricity generating cost with a single CO_2 market is expected to be lower than with separate CO_2 markets. A single CO_2 market equates marginal CO_2

[27] See discussion on exogenous state variables in Section 4.2, as well as the additional details in Section A.5.

[28] See the June 2014 CPP proposed rule technical support documentation (TSD) at `https://www.epa.gov/cleanpowerplan/clean-power-plan-proposed-rule-technical-documents`. The relevant TSD spreadsheet provides state-specific growth rates for renewable energy for 2020–2029. We assume that the average growth rate for 2020–2029 holds for the entire period of our simulations. Moreover, we assume that nuclear capacity does not change.

[29] Borenstein et al. (2016) argue that extreme price outcomes are likely in most cap-and-trade markets for greenhouse gas (GHG) emissions for two main reasons. The first is GHG emissions volatility. The second is the low price elasticity of GHG abatement over the price range generally deemed to be acceptable. Recognizing the problems created by uncertainty in emissions permit prices, hybrid mechanisms that combine caps on emissions and price collars (both lower and upper bounds) have been proposed. See their Section I and the references therein.

abatement costs across markets, leading to lower overall compliance costs. Insights from the trade literature, however, tell us that an integrated *product* (electricity) market can mitigate inefficiencies associated with separate CO_2 markets as long as production from markets with high CO_2 prices can be reallocated to markets with low CO_2 prices, all else equal.

We solve for the equilibrium of the electricity and CO_2 market(s) as a function of BAT capacity. In this analysis, we assume that BAT capacity is fixed at $K \in [1000, 60000]$ from 2013 onwards. Panel (a) of Figure 11 plots the present discounted value of electricity generating cost for single and separate CO_2 markets as a function of BAT capacity. Panel (b) plots the difference in costs instead, which is our measure of static inefficiency. As expected, conditional on having the same BAT capacity (hence, total capacity), cost with separate CO_2 markets is generally higher than with a single CO_2 market. Interestingly, both costs decrease as BAT capacity increases, reflecting the fact that BAT capacity is more efficient and emit less CO_2 than the existing capacity.

Looking at the difference in costs in panel (b), we see that static efficiency first increases as BAT capacity increases, and then decreases after some point. The initial increase is due to the assumption that CO_2 prices are constrained to be below \$100 per ton. When BAT capacity is low, CO_2 markets during peak-hours and summer months tend to induce CO_2 prices that hit this upper bound. Thus, the lower BAT capacity is, the more instances the upper bound is binding which then induces a positive relationship between BAT capacity and static inefficiency. However, as BAT capacity increases, there will be a point where BAT capacity is sufficient such that there is no market where the upper bound on CO_2 prices binds. Once this occurs, the higher the BAT capacity is, the lower the static inefficiency. This negative relationship between BAT capacity and static inefficiency reflects the idea that relaxing the capacity constraint facilitates reallocation of production which then mitigates the inefficiency with separate CO_2 markets.

We find that the maximum static inefficiency is \$7.8 billion which occurs at BAT capacity of 30,000 MW. This difference is about 50% of the environmental compliance cost, which is the difference in electricity generation plus investment costs with and without the CPP assuming separate CO_2 markets. Finally, static inefficiency goes to zero for sufficiently large BAT capacity (more than 50,000 MW). In this case, capacity constraints no longer bind and electricity generation costs with single and separate CO_2 markets are the same.

5.2 Dynamic Analysis: Optimal Investment

We now compare outcomes taking into account firms' optimal investment. The model we used for estimation assigns the top ten firms in PJM as strategic firms in terms of the investment decision. For computational reasons, we instead analyze simpler modeling scenarios. In the first scenario, we solve a model where the ten strategic firms fully coordinate investment hence acting as a single firm. In the second scenario, to add an element of competition, we solve a model where the ten firms are assigned into two coalitions and decide on optimal investment with maximizing the coalition's present value discounted profit in mind. We also simulate the following two scenarios: (i) a social planner decides on investment and (ii) firms are nonstrategic in the sense that they invest as long as the marginal benefit is higher than the cost of capital. Note that in all scenarios, we maintain the same set of plants that we considered during estimation, hence preserving plant-level heterogeneity across the region.

The key message that inefficiency with separate CO_2 markets is completely mitigated even after accounting for the additional cost of investment is robust across all scenarios. In what follows, we first discuss the scenarios with the social planner and nonstrategic investment. These two scenarios provide a useful benchmark to frame the discussion of the other two scenarios with strategic investment.

5.2.1 Social Planner and Nonstrategic Investment

The social planner chooses investment to maximize the present value discounted sum of social surplus. In maximizing social surplus, the planner takes into account consumer surplus from electricity consumption, industry profits, as well as damages from CO_2 emissions calculated assuming the social cost of carbon is \$37 per metric ton. It is useful to discuss the social planner scenario vis-a-vis the scenario where investment is chosen to maximize the present discounted sum of consumer surplus and profits, *without* internalizing damages from CO_2 emissions. As Bushnell et al. (2017b) argue, this latter scenario is equivalent to a scenario with competitive investment. We refer to this latter scenario as the scenario with *nonstrategic investment*.

The steady state (2030) BAT capacity is 34,250 MW in the case of the social planner (Table 9). In the case of nonstrategic investment, BAT capacity is 48,150 MW with a single CO_2 market and 51,300 MW with separate CO_2 markets. Since that BAT capacity is higher with nonstrategic investment, electricity prices are lower—\$28 per MWh (single CO_2 market) and \$27 per MWh (separate CO_2 markets)—compared to \$34 per MWh in the case of the social planner. However, cheaper electricity prices in the case of nonstrategic investment comes at a cost. Average CO_2 emissions in the case of the social planner are 374.2 million tons while emissions assuming nonstrategic investment are about 10% higher. The present value discounted welfare for the social planner is \$1,142 billion. In the case of the nonstrategic investment, the present value discounted welfare is essentially identical in the two regulatory regimes: \$1,134 billion with a single CO_2 market and \$1,133 billion with separate CO_2 markets.

The difference in welfare between the two scenarios is driven by how damages from CO_2 emissions enter the objective function for investment. Unlike in the social planner case, nonstrategic investment does not fully internalize the damages from emissions. Even with a single CO_2 market, since the BAT capacity is not subject to a CO_2 price, there will be overinvestment leading to emissions leakage (Fowlie, 2009). With separate CO_2 markets, the incentive to invest is even stronger, exacerbating overinvestment and the emissions leakage problem. Nonetheless, the difference in welfare between the two regulatory regimes is small and is not driven by the lack of coordination of the CO_2 markets across the states *per se* but by the regulatory treatment of investment.[30] The present value discounted electricity generation costs is actually lower (\$58.5 billion) with separate CO_2 markets than with a single CO_2 market (\$59.5 billion) though the difference is quite small.

5.2.2 Strategic Investment

Single Firm. In this scenario, the ten strategic firms fully coordinate investment to maximize the sum of their present value discounted profits. With a single CO_2 market, the steady state BAT capacity is suppressed to 4,000 MW raising the average electricity price to \$89 per MWh. In contrast, with separate CO_2 markets, the steady state BAT capacity is 11,300 MW and the average electricity price is \$86 per MWh. Electricity generation cost is lower with separate CO_2 markets (\$185.9 billion) that with a single CO_2 market (\$212.9 billion). Although investment cost is higher with separate CO_2 markets, the difference in the investment costs between the two regulatory regimes is smaller compared to the difference in the electricity generation costs. As a result, the overall cost is actually lower with separate CO_2 markets. Moreover, the average CO_2 emissions are in fact lower with separate CO_2 markets (258.1 million tons) than with a single CO_2 market (270.1 million tons), contrary to what one expects with emissions leakage. This reduction in emissions stems from investment in generating units that emit less per unit of electricity than the existing units.

Present value discounted welfare with separate CO_2 markets is \$1,139 billion, which is larger than its counterpart with a single CO_2 market (\$1,130 billion). It may seem surprising that a setting with an inherent inefficiency—absence of a single market for correcting the externality—yield higher welfare. However, this inefficiency is mostly static in nature when we do not take into account the incentives to invest. The scenario with separate CO_2 markets yield higher welfare because there is a second distortion that is corrected: profit-maximizing *strategic* firms take into account the effect of investment on the evolution of electricity prices. Since, all else equal, an increase in capacity today leads to a decrease in future prices, firms

[30] See Section A.6 for a discussion of a different regulatory treatment of new plants.

have a strong incentive to withhold investment. The additional incentive to invest in the case of separate CO_2 markets leads to *higher* welfare since it brings us closer to the socially optimal level of BAT capacity.

Two-firm Game. We now relax the assumption of fully coordinated investment by introducing competition. For computational reasons, we study a two-firm (leader-follower) investment game.[31] We create two "coalitions" of strategic firms by allocating all the existing plants owned by the strategic firms equally (also in terms of characteristics) into two groups. We treat one coalition as the leader (invests first) and one coalition as the follower (invests second). Each coalition decides strategically on investment taking into account profits earned from the plants it owns and how investment changes endogenous state variables, including BAT capacity of all firms in both coalitions. We maintain the assumption of competitive behavior in both the electricity and CO_2 markets, and solve the stage game by finding the market clearing prices. With a competitive wholesale electricity market, the equilibrium quantity and price are not affected by our assumption on the number of investing firms, conditional on the set of plants in the market.

Introducing competition weakens firms' incentives to strategically withhold investment in order to raise prices. It is still the case, however, that the two-firm game implies underinvestment. Total BAT capacity is 10,400 MW with a single CO_2 market, and it is 17,850 MW with separate CO_2 markets. Although these capacity levels are lower than the socially optimal level, they exceed their counterpart with fully coordinated investment. In this two-firm game, the players are able to raise electricity prices above efficient levels but not as much as the monopolist does. The electricity prices are now \$72 per MWh (single CO_2 market) and \$67 per MWh (separate CO_2 markets).

Consistent with our earlier findings, generation cost is lower with separate CO_2 markets (\$128.9 billion) than with a single CO_2 market (\$161.8 billion). Moreover, the difference in investment cost (\$24.6 billion versus \$14.5) is small enough such that on net, overall costs is lower with separate CO_2 market. Finally, separate CO_2 markets also yield higher total welfare. The difference in total welfare between the two regulatory regimes is \$3.8 billion and is explained by the fact that investment rates are closer to socially optimal levels with separate CO_2 markets. Moreover, competition has the effect that most of the new capacity is built earlier even when compared to the case of a social planner. This is the result of the leader's effort to preempt its rival by investing early in the game.

[31]See Section A.5.2 for details on computation.

6 Conclusion

In this paper, we show that separate markets for an environmental externality, which may emerge due to lack of regulation coordination across jurisdictions, yield almost the same outcomes as a single market that emerges if coordination is possible. The main driving force behind our findings is investment when firms participate in an integrated product market, which mitigates some of the inefficiencies associated with separate markets for the externality that emerge in the absence of coordinated regulation.

Our workhorse is a dynamic structural model of production and investment for the largest wholesale electricity market in the world, the Pennsylvania-New Jersey-Maryland (PJM) Interconnection. The environmental regulation of interest entails targets for carbon dioxide (CO_2) emissions from electricity generation achieved via a market for emission permits with and without coordination across states participating in PJM. In the case of coordinated regulation, there is a single PJM-wide CO_2 market. With uncoordinated regulation, there are separate CO_2 markets, one for each of the states.

Our model preserves the rich plant-level cost heterogeneity in the data while being tractable enough to evaluate market outcomes across the two regulatory regimes. We achieve tractability by assuming that market participants invest in the best available technology (BAT) at the time of the investment, which is consistent with the current interpretation of the Clean Air Act. In our setup, CO_2 emissions from BAT capacity are exempt from the targets. As a result, the location of firms' investment is irrelevant—only the total amount of investment matters. An interesting direction for future research is to relax this assumption and explore the geographic dimension of firms' investment choices.

Given the recent developments in U.S. environmental policy, the future of federal regulations aiming to curb CO_2 emissions is unclear. Therefore, an important question that can be answered using our framework is whether states have unilateral incentives to adopt emission restrictions in the absence of any federal mandate. For example, Abito (2019b) uses our model to analyze the impact on PJM when Pennsylvania unilaterally joins the Regional Greenhouse Gas Initiative. The potential benefit of unilateral adoption would be to provide incentives for investment in more efficient capacity, as in the case with uncoordinated regulation, which would bring production into states that adopt those restrictions. It is also important to emphasize the potential benefits for consumers in states that do not adopt any emissions regulations since more efficient capacity may decrease electricity prices for the whole region. Any careful analysis should take into account the interaction between the product and externality markets and the adjustments that occur beyond the short-run, such as investment in new capacity..

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7 Tables

Table 1: Capacity by source

year	coal	gas	nuclear	oil	hydro	solid waste	wind	total
2005	67.8	45.0	31.2	11.8	7.0	0.5		163.5
2006	66.5	47.0	30.0	10.7	7.1	0.6		162.1
2007	66.2	47.6	30.9	10.6	7.4	0.7	0.2	163.5
2008	66.9	48.1	30.4	10.7	7.4	0.7	0.3	164.3
2009	68.1	48.9	30.8	10.7	7.9	0.7	0.7	167.3
2010	67.9	48.5	30.5	10.2	8.0	0.7	0.7	166.5
2011	75.1	50.6	32.6	11.3	8.0	0.7	0.7	178.8
2012	76.1	52.0	32.9	11.5	7.8	0.7	0.7	182.0

(a) MW (thousands)

year	coal	gas	nuclear	oil	hydro	solid waste	wind	total
2005	41.5	27.5	19.1	7.2	4.3	0.3		100
2006	41.0	29.0	18.5	6.6	4.4	0.4		100
2007	40.5	29.1	18.9	6.5	4.5	0.4	0.1	100
2008	40.7	29.3	18.5	6.5	4.5	0.4	0.2	100
2009	40.7	29.2	18.4	6.4	4.7	0.4	0.4	100
2010	40.8	29.1	18.3	6.1	4.8	0.4	0.4	100
2011	42.0	28.3	18.2	6.3	4.5	0.4	0.4	100
2012	41.8	28.6	18.1	6.3	4.3	0.4	0.4	100

(b) MW (%)

Note: based on PJM state of the market reports available at http://www.monitoringanalytics.com/reports/PJM_State_of_the_Market/2018.shtml. For additional details, see Section 2.1.

Table 2: Clean Power Plan mass-based targets (million short tons)

state	2022	2023	2024	2025	2026	2027	2028	2029	2030
DE	5.524	5.355	5.166	5.072	4.971	4.846	4.806	4.762	4.712
IL	32.087	30.907	29.371	28.737	28.050	27.224	26.686	26.102	25.458
IN	30.510	29.389	27.931	27.328	26.676	25.892	25.382	24.829	24.218
KY	14.327	13.793	13.091	12.805	12.494	12.122	11.871	11.598	11.297
MD	18.197	17.518	16.626	16.263	15.869	15.396	15.076	14.730	14.348
NC	1.333	1.286	1.227	1.201	1.174	1.140	1.121	1.101	1.078
NJ	16.678	16.222	15.778	15.519	15.241	14.892	14.858	14.819	14.766
OH	92.147	88.825	84.565	82.775	80.838	78.501	77.061	75.499	73.770
PA	110.196	106.388	101.664	99.598	97.364	94.653	93.188	91.596	89.822
VA	32.341	31.334	30.195	29.638	29.038	28.297	28.040	27.757	27.433
WV	65.266	62.818	59.587	58.277	56.857	55.154	53.986	52.720	51.325

Note: The mass-based targets reported in this table are based on the supporting data file for CPP compliance from PJM (2016) and are based on electric generating units in the PJM footprint for each state noting that PJM covers only parts of IL, IN, KY, and NC. The rate-based targets reported in panel (b) are from the Appendix 5-State Goals sheet in CPP State Goal Visualizer spreadsheet. A detailed spreadsheet with the calculation of the mass-based targets was provided to the authors by PJM.

Table 3: Clean Power Plan baseline generation for 2012

	MWh (thousands)				MWh (percent)			
state	coal	gas	oil	total	coal	gas	oil	total
DE	1,413	6,672	1,079	9,164	15.41	72.81	11.77	100
IL	84,488	10,001	0	94,489	89.42	10.58	0.00	100
IN	96,335	12,839	3	109,178	88.24	11.76	0.00	100
KY	84,364	3,092	0	87,456	96.46	3.54	0.00	100
MD	16,298	677	2,892	19,867	82.04	3.41	14.56	100
NC	54,920	25,520	0	80,440	68.27	31.73	0.00	100
NJ	2,603	33,665	173	36,440	7.14	92.38	0.47	100
OH	86,345	23,687	384	110,416	78.20	21.45	0.35	100
PA	87,055	57,420	1,662	146,137	59.57	39.29	1.14	100
VA	15,671	36,292	344	52,307	29.96	69.38	0.66	100
WV	70,078	0	0	70,078	100.00	0.00	0.00	100

Note: The numbers in this table are based on existing and under-construction electric generating units in the PJM footprint for each state in 2012 noting that PJM covers only parts of IL, IN, KY, and NC. For units under construction, the baseline generation is calculated as capacity factor $\times$ $8,760 \times$ summer capacity with a capacity factor of 0.60 for coal- and 0.55 for gas-fired units. A detailed spreadsheet with the unit-level baseline generation was provided to the authors by PJM.

Table 4: List of strategic firms

Abbreviation	Full Name
AEP	American Electric Power
AES	Applied Energy Services
DOM	Dominion
DUKE	Duke
EXE	Exelon
FE	First Energy
GEN	Genon
NRG	NRG
PPL	Pennsylvania Power and Light
PSEG	Public Service Enterprise Group

Table 5: Fringe supply

Variable	(1) Log	(2) Level	(3) Sq. Root	(4) Cb. Root
Price	4,485.9443***	99.5049***	1,432.4503***	4,035.5585***
	(1,274.8795)	(34.6896)	(419.2847)	(1,127.8839)
CDD	-97.4268	-124.8973	-124.4694	-118.9736
	(137.1025)	(162.0668)	(150.4534)	(145.9993)
CDD Sq.	11.1935	9.9947	10.3957	10.6223
	(6.8215)	(7.7162)	(7.2300)	(7.0770)
HDD	14.7302	52.9018	45.2620	37.9005
	(61.2242)	(87.4259)	(74.2798)	(69.3752)
HDD Sq.	-0.9712	-2.0324	-1.8877	-1.6781
	(1.6612)	(2.5088)	(2.0611)	(1.8983)
Constant	-2,465.7182	2,689.1103***	534.2531	-1,398.0739
	(1,762.4441)	(682.6402)	(1,054.6609)	(1,489.6102)
Observations	119	119	119	119
R-squared	0.7979	0.7487	0.7694	0.7783
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

Note: The table presents two-stage least squares coefficients estimates for various functional form specifications of price using monthly data for 2003–2012. In all 4 specifications, the dependent variable, fringe supply, is in levels, and we include year and month (seasonal) fixed effects. We use CDD (HDD) to refer to cooling (heating) degree days. The results reported in the paper are based on the log specification reported in column (1). Standard errors in parentheses are corrected for heteroskedasticity. The asterisks denote statistical significance as follows: 1% (***), 5%(**), 10%(*).

Table 6: Target policy equation

Variable	(1) coal	(2) gas
Entry	1,070.1457***	442.6195***
	(335.6758)	(101.1281)
Capacity own	0.9547***	1.0184***
	(0.1292)	(0.0832)
Capacity rival	-0.0057	-0.0090
	(0.0104)	(0.0100)
Price coal	-361.3379**	161.7350
	(157.0343)	(183.6855)
Price gas	225.2231*	8.1209
	(118.0989)	(18.8208)
Permit price SO_2	-444.6747**	-118.9773*
	(222.5244)	(71.4921)
Permit price NO_x	-1,940.8544*	370.9387
	(1,158.7378)	(558.2496)
Observations	169	280
R-squared	0.4571	0.6714

Note: The estimates are based on annual operator-level data for 2003–2012. Standard errors in parentheses are corrected for heteroskedasticity. The asterisks denote statistical significance as follows: 1% (***), 5%(**), 10%(*).

Table 7: Cost per megawatt of gas-fired capacity ($/MW)

Fuel	est.	s.e.
gas	1,389,957	32,345

Note: The reported standard error is calculated resampling moment inequalities and ignores any 1st-stage estimation error.

Table 8: Investment in gas-fired capacity

Company	Size	Counts
AEP	0.000	0
AES	2.398	12
DOM	0.000	0
DUK	0.000	0
EXE	2.843	15
FE	1.704	7
GEN	0.573	2
NRG	2.552	12
PPL	0.852	3
PSEG	0.000	0
TOTAL	10.921	51

Note: The numbers reported are for 2013–2062. A company is assumed to invest once a year. For example, AES invested 12 times during 2013–2062. Size is measured in thousand megawatt (MW).

Table 9: Summary of outcomes for alternative investment scenarios

Scenario	BAT Capacity MW	Electricity Price $/MWh	Generation Costs $ billion	Investment Costs $ billion	CO_2 Emissions tons million
SOCPLAN	34,250	34	75.4	30.6	374.2
NST-SIN	48,150	28	59.5	47.2	414.3
NST-SEP	51,300	27	58.5	48.9	419.3
1F-SIN	4,000	89	212.9	1.3	270.1
1F-SEP	11,300	86	185.9	5.1	258.1
2F-SIN	10,400	72	161.8	14.5	298.5
2F-SEP	17,850	67	128.9	24.6	311.7

Note: BAT refers to best available technology. We report a quantity-weighted average price of electricity and a quantity-weighted average of CO_2 emissions. The present discounted dollar values are calculated using a discount factor of 0.90 and assuming that the 2030 values correspond to the steady state values. A brief description of the scenario abbreviations is available in Table 10.

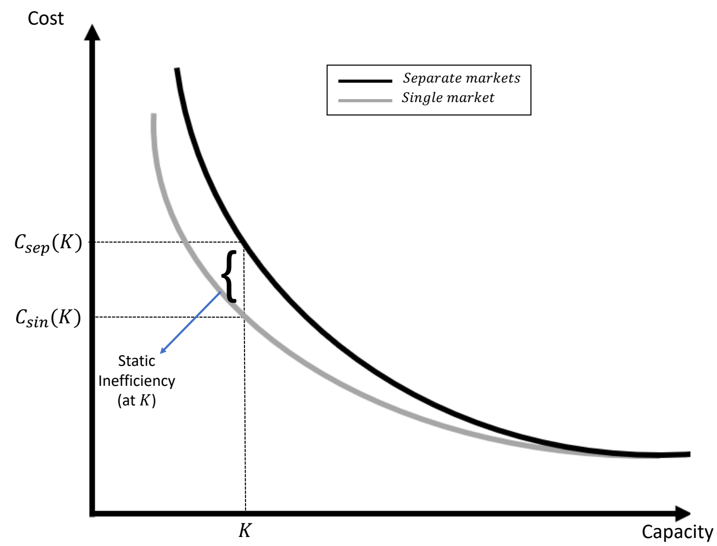
Table 10: Description of alternative investment scenarios

Abbreviation	Description
SOCPLAN	Social planner
NST-SIN	Non-strategic investment, single CO_2 market
NST-SEP	Non-strategic investment, separate CO_2 market
1F-SIN	Single-firm investment, a single CO_2 market
1F-SEP	Single-firm investment, a separate CO_2 markets
2F-SIN	Two-firm investment game, single CO_2 market
2F-SEP	Two-firm investment game, separate CO_2 markets

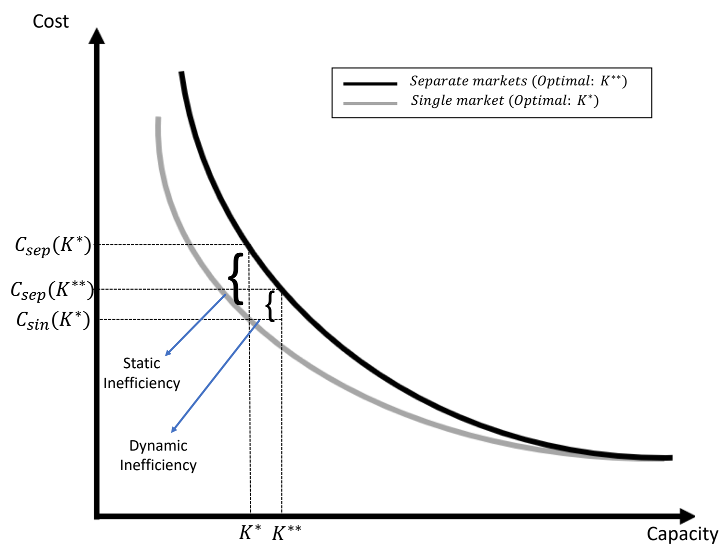
Note: the table provides a brief description of the alternative investment scenarios that pertain to different market structures and regulatory regimes and are discussed in detail in Section 5.

8 Figures

Figure 1: Static versus Dynamic inefficiency



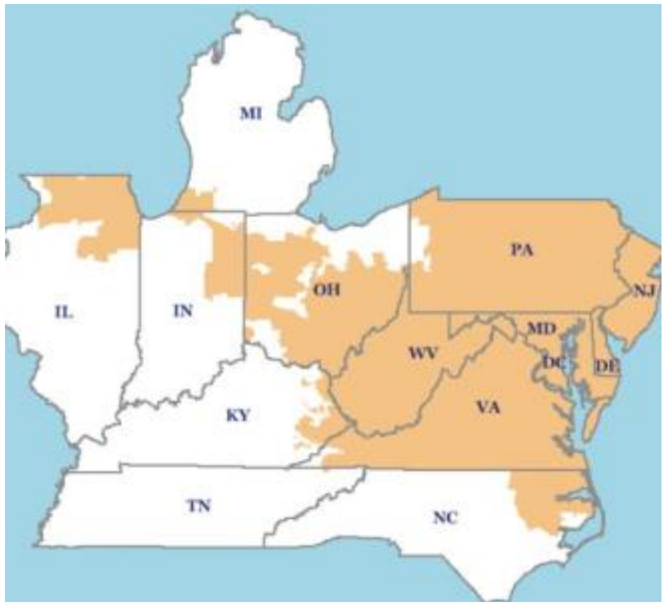
(a) Static analysis



(b) Dynamic analysis

Note: The figure shows electricity generation cost with a single and separate externality markets for different capacity levels. Panel (a) refers to the static analysis for which we compare costs holding fixed the level of capacity. Panel (b) refers to the dynamic analysis where we take into account optimal investment levels. Optimal capacity with a single market (K^*) is lower than the optimal capacity with separate markets (K^{**}) due to the greater investment incentives in the latter. Accounting for optimal investment decreases the difference in costs between the two types of markets from $C_{sep}(K^*) - C_{sin}(K^*)$ to $C_{sep}(K^{**}) - C_{sin}(K^*)$.

Figure 2: Area covered by the Pennsylvania-Jersey-Maryland (PJM) Interconnection



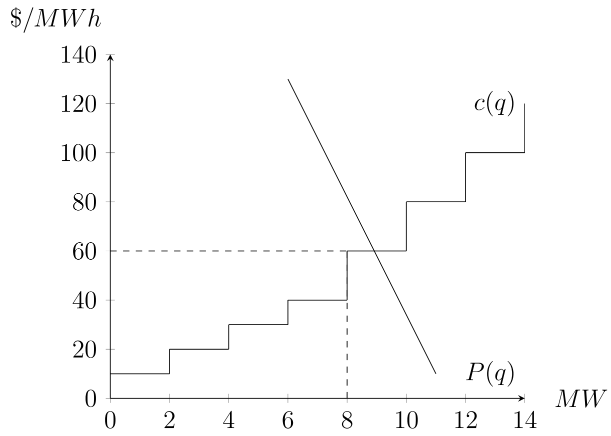
Source: http://ieefa.org/pjms-reform/

Figure 3: Overview of the model timing

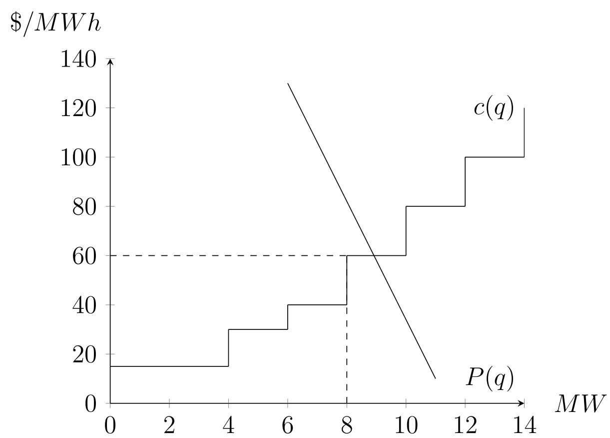
$$\begin{array}{ccccc} 2012 & \longrightarrow & 2013 & \longrightarrow & 2014 \\ & \begin{array}{c}\text{Demand parameters}\\ \underbrace{\text{Cost functions}}_{\text{Electricity Market}}\end{array} & \begin{array}{c}\Big\downarrow\\ \textbf{Investment}\end{array} & \begin{array}{c}\text{Demand parameters}\\ \underbrace{\textbf{Cost functions}}_{\text{Electricity Market}}\end{array} & \end{array}$$

Note: the bold text emphasizes the fact that investment in 2013 affects the cost functions in 2014.

Figure 4: Equilibrium invariance with inframarginal units



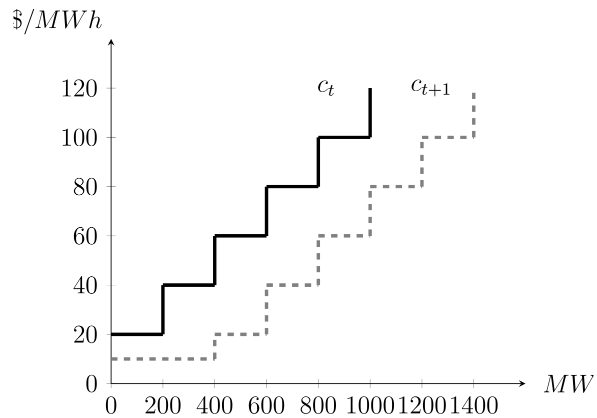
(a) Demand and supply



(b) Invariance to averaging

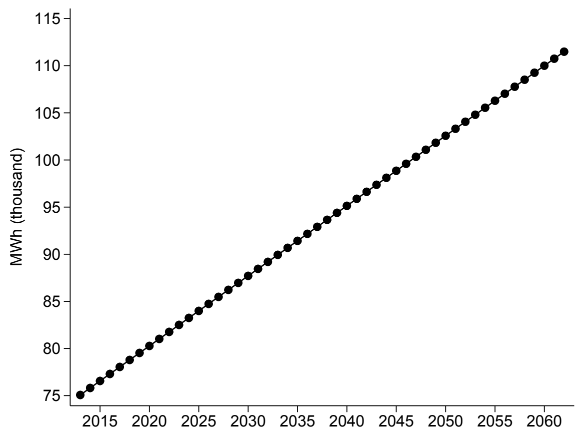
Note: Let the first two steps in panel (a) represent new capacity (i.e. capacity added after 2013). Panel (a) illustrates the market equilibrium when we retain all the information each time we add a new plant. Panel (b) instead only keeps track of the cumulative size of added capacity and updates a weighted-average cost of these new additions. As long as new capacity is infra-marginal, equilibrium quantities, prices and profits are invariant to averaging of these plants.

Figure 5: Updating the marginal cost curve

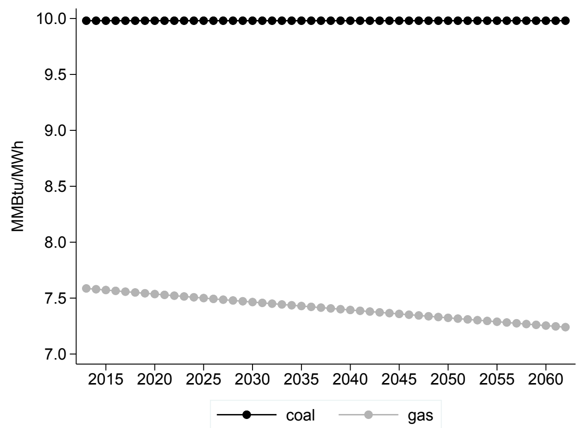


Note: The step function c_t (black solid line) indicates the marginal cost curve prior to investment at time t and is constructed by ordering available sources to serve demand in terms of their marginal costs. The sources with the lowest (highest) costs are ordered first (last). The step function c_{t+1} (gray dashed line) indicates the marginal cost curve following a hypothetical investment of 400 MW in best available technology with a cost of $10/MWh. The vertical distance between the two curves at their origin shows the improvement in marginal costs between the available technology at time t and time $t+1$.

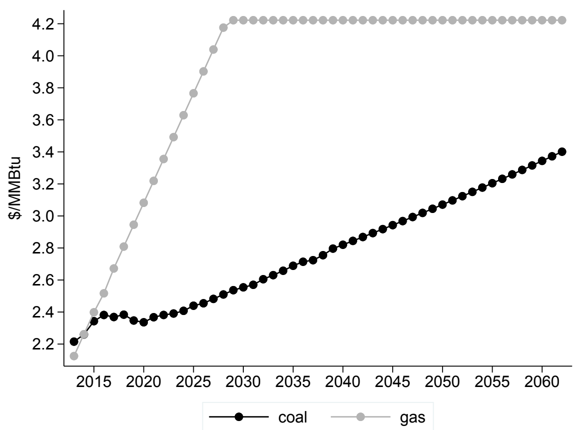
Figure 6: Paths of exogenous variables, 2013–2062



(a) Residual demand intercept ($\widehat{\alpha}_t$)

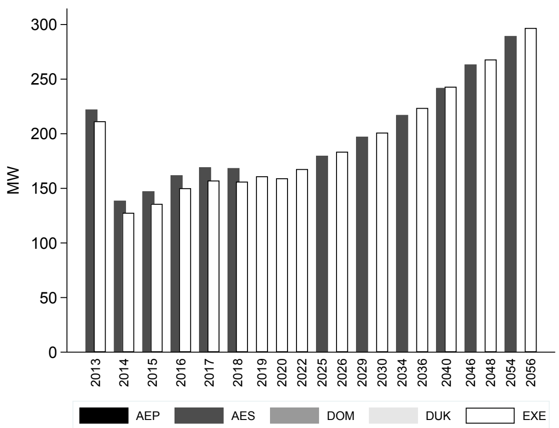


(b) Heat rates for new investment

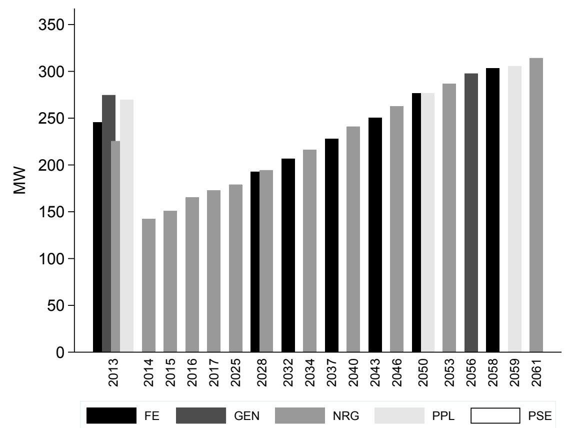


(c) Fuel prices

Figure 7: BAT Investment in gas-fired capacity, 2013–2062



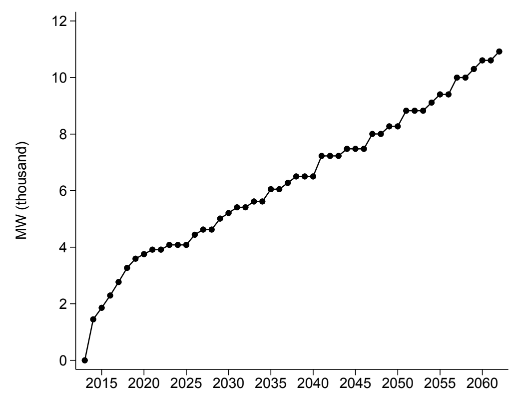
(a) 1st group



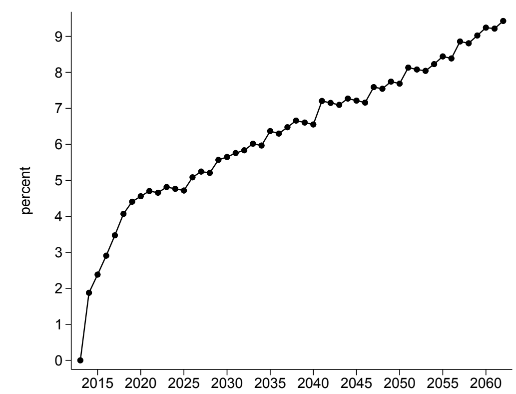
(b) 2nd group

Note: BAT refers to best available technology. The figure shows only years for which there is investment. We divide firms in two groups and report their investment levels in two panels so that the figure is more legible. In the 1st group, and consistent with the entries of Table 8, only Applied Energy Services (AES) and Exelon (EXE) invest.

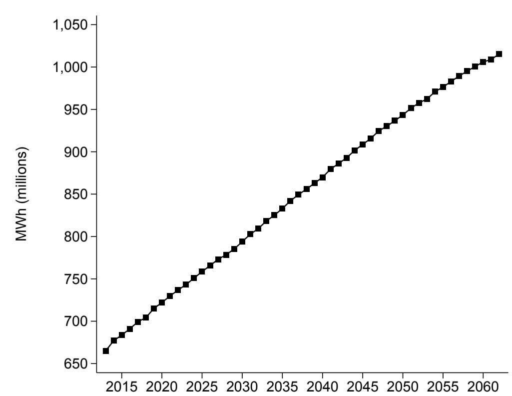
Figure 8: Paths of endogenous variables, 2013–2062



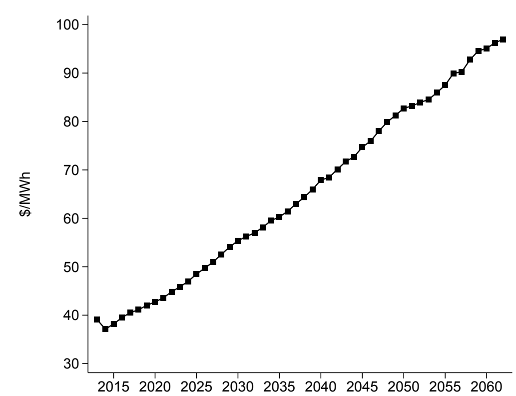
(a) BAT capacity



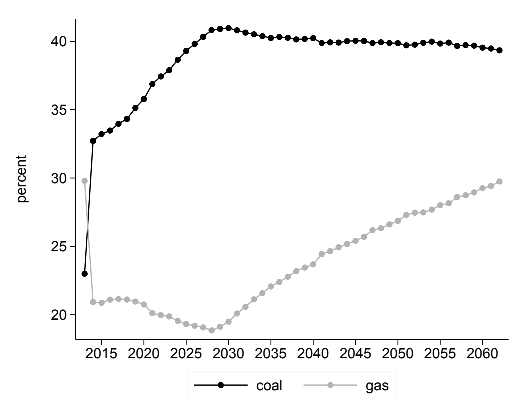
(b) BAT capacity: generation %



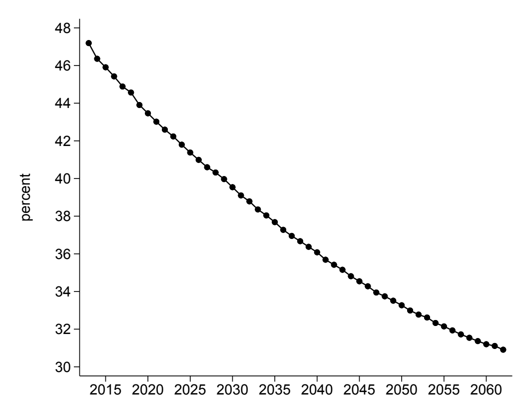
(c) electricity generation



(d) electricity price



(e) electricity generation % from coal and gas



(f) electricity generation % from other fuels

Note: BAT refers to best available technology.

Figure 9: Electricity prices implied by the model compared to NYMEX futures

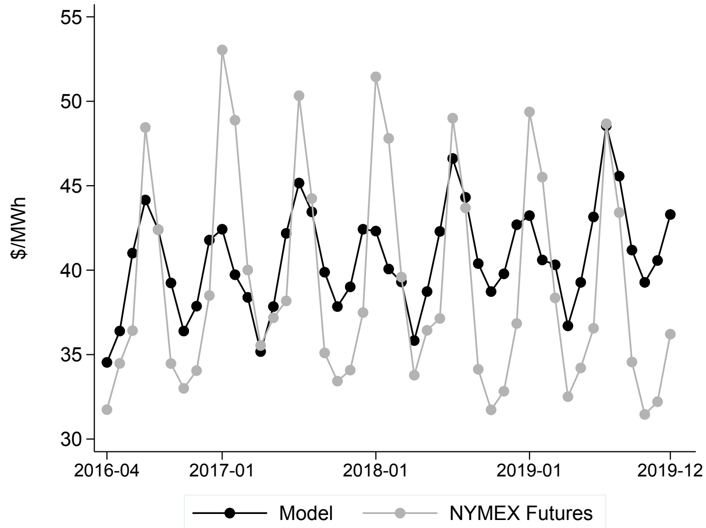
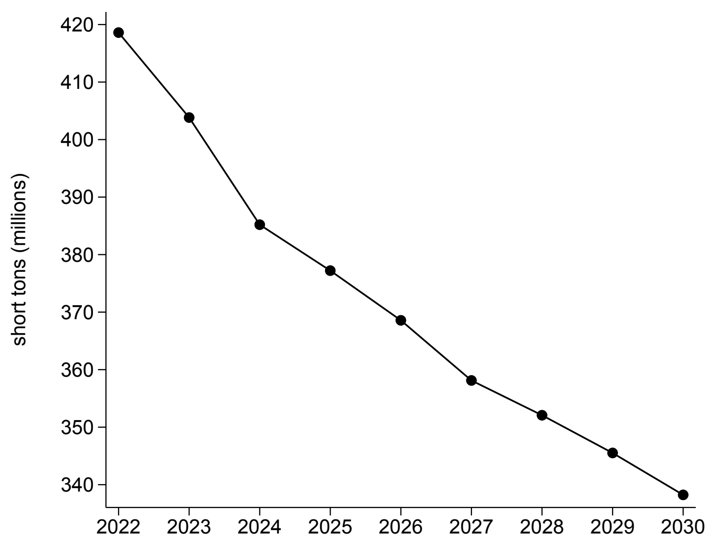
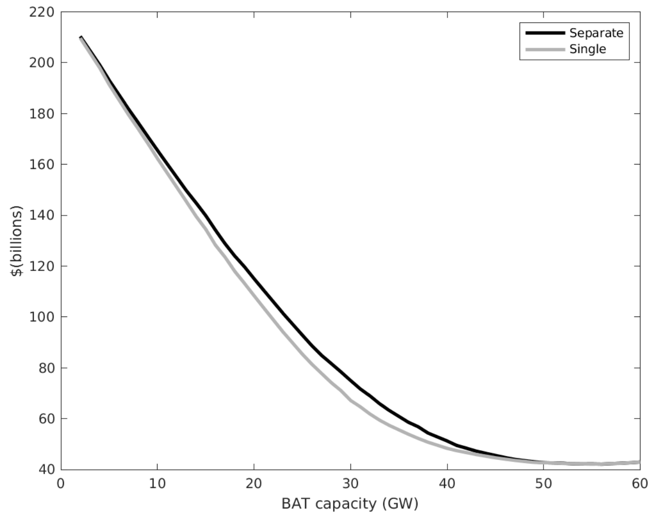


Figure 10: Regional CPP mass-based targets

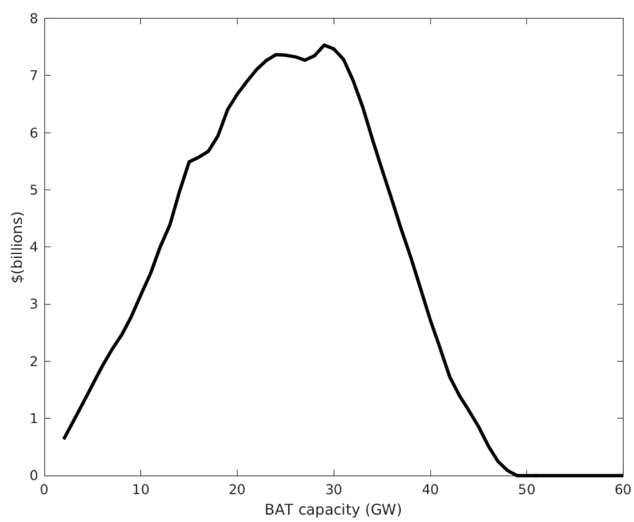


Note: The mass-based target in this figure is based on the supporting data file for CPP compliance from PJM (2016) and are based on electric generating units in the PJM footprint for each state noting that PJM covers only parts of IL, IN, KY, and NC. We plot the sum of state mass-based targets from panel (a) of Table 2.

Figure 11: Static analysis



(a) Cost of generating electricity



(b) Static inefficiency

Note: Panel (a) plots the present discounted value of electricity generation costs for the separate and single CO_2 markets scenarios as a function of best available technology (BAT) capacity. We keep the BAT capacity fixed from 2013 onwards for both scenarios in this analysis. Panel (b) plots the difference in present discounted value of electricity generation costs between the two scenarios as a function of BAT capacity.

A Online Appendix

NOT FOR PUBLICATION

A.1 Data

Our empirical analyses require us to track the expansion of the PJM footprint over time due to zone additions. We identified the additions using publicly available data on estimated hourly load by region in the PJM Markets & Operation website, as well as reviewing the PJM State-of-The-Market (SOM) Reports from Monitoring Analytics; the reports are also publicly available.[32]

We identified firms using the operator and owner fields in the EIA-860 data, which we complemented with information from the Edison Electric Institute (EEI), the companies' websites and annual reports, and the SNL merger database.[33] We identified plants in the PJM footprint using the approach in Knittel et al. (2019).

Monthly plant-level fuel prices are available from EIA-423, FERC-423, and EIA-923. We also obtained access to confidential data for non-utility plants. Generation and fuel consumption data are from EIA-906/920 and EIA-923 beginning in 2008.[34] The annual data on plant operating expenses are from SNL.[35]

Annual plant-level capacities are from EIA-860. The capacities in EIA-860 are recorded at the electric generating unit level and a power plant may have several units. When needed, we sum the capacities of all units that belong to the same plant. We use the primary energy source for each unit to calculate coal- and gas-fired capacities.[36] We account for intermittency of renewables by using the capacity factors from Table 6.7.B from the EIA Electric Power Monthly for December 2014, averaged for the period 2008 through 2013. These factors are highly comparable to the ones we identified in PJM reports regarding resource adequacy planning.

System-wide real-time metered load data as consumed by the service territories and locational marginal prices are available from the PJM website. The data are available at

[32] See http://www.pjm.com/markets-and-operations/energy/real-time/loadhryr.aspx and http://www.monitoringanalytics.com/reports/PJM_State_of_the_Market/2015.shtml. Major zone additions took place in 2004 and 2005 when Comed, Dayton, American Electric Power, Duquense, and Dominion joined PJM. The next major additions were in 2011 and 2012, when American Transmission Systems (First Energy) and Duke Energy Ohio & Kentucky joined PJM. The latest addition was East Kentucky Power Cooperative in 2013.

[33] See http://www.eei.org/about/members/uselectriccompanies/Pages/usmembercolinks.aspx for the U.S. Member Company links of EEI. Note that we have also taken into account mergers that took place during the period that is relevant for our analysis (e.g., the Mirant/RRI merger to form GenOn Energy in Dec-2010, and the NRG Energy/GenOn Energy merger in Dec-2012.

[34] See http://www.eia.gov/electricity/data/eia423/ and http://www.eia.gov/electricity/data/eia923/.

[35] It is the field Unit Non-Fuel O&M reported under the Whole Plant Operating Annual-Operating Expenses in the Power Plants database.

[36] See http://www.eia.gov/electricity/data/eia860/. The total generating capacity for PJM calculated using these data is within 5% of the generating capacity reported in PJM State-of-the-Market Reports for 2003–2012.

an hourly frequency. In the case of load, we use total load during a month. In the case of prices, we calculate a monthly load-weighted average. We calculate net imports using data on real-time scheduled interchange from PJM for the late part of the analysis.[37]

The SO_2 and seasonal NO_x permit prices are from Evolution Markets, a permit brokerage firm we identified from the EPA website.[38] The Weather used in the estimation of the fringe supply equations are from the National Oceanic and Atmospheric Administration (NOAA).[39]

A.2 Descriptive Statistics

Tables A1 and A2 provide information regarding the number of plants, generation, and capacity that the strategic firms account for between 2003 and 2012. The number of plants for the strategic firms increased from 47 in 2003 to 109 in 2012. We also see an increase in the number of both coal- and gas-fired units for strategic firms. In the former case, we see an increase from 55 to 135 units. In the latter case, we see an increase from 107 to 262 units. The strategic firms' share of coal-fired (gas-fired) capacity increased (decreased) from 77% (60%) in 2003 to 85.5% (50%) in 2012. During this period, the strategic firms' share of coal- (gas-) fired generation increased from 78% (42%) to 87% (51%).

Summary statistics related to the cost functions for each of the strategic firms in our model for 2012 are available in Table A3. We report summary statistics for 2012 given that this is the year that is relevant for the estimation of our structural model using monthly unit-level observations noting that a power plant may have more than one electric generating unit.[40] A casual look at the table shows substantial variation both across and within firms, which we preserve when we estimate our dynamic model.

In Table A4, we show the coal- and gas-fired capacity for each of the 10 strategic firms for 2003–2012. Several patterns emerge that offer support for our modeling assumptions. Investment is lumpy and, in general, we see more action in gas-fired capacity than in coal-fired capacity. Capacity changes take place only in a subset of years for each of the strategic firms, and they account for a notable fraction of existing capacity. For example, AEP increased its coal-fired capacity from around 15,300 MW in 2006 to 21,000 MW in 2007, an increase

[37]See http://www.pjm.com/markets-and-operations/ops-analysis/historical-load-data.aspx and http://www.pjm.com/markets-and-operations/energy/real-time/lmp.aspx, for the load and price data, respectively. See http://www.pjm.com/markets-and-operations/ops-analysis/nts.aspx for net tie schedule (NTS) data. Erin Mansur generously provided us all NTS data for 1999–2010 with the exception of 2007–2009, which we are missing. We impute values for each month in this 3-year period using the average of 2006 and 2010. For example, we use the average of Jul-2006 and Jul-2010 to construct the monthly value for Jul-2007.

[38]See http://www.evomarkets.com/environment/emissions_markets.

[39]See http://www.ncdc.noaa.gov/cdo-web/search/#t=secondTabLink

[40]The all-inclusive cost of 1 MWh of electricity (cost) exhibit variation by unit and month. The fuel prices exhibit variation by plant and month. The VOM costs and heat rates exhibit variation by plant only.

of approximately 37%. AEP also increased its gas-fired capacity from 1,700 MW in 2006 to 3,237 MW in 2012. As another example, the gas-fired capacity of Genon (GEN) increased from 1,919 MW in 2008 to 2,839 in 2009. Moreover, the generation portfolio differs across firms. AEP dominates coal followed by First Energy (FE) and Genon. The three companies account, on average, for 29%, 23%, and 14% of the coal-fired capacity in each year between 2003 and 2012. PSEG, Dominion (DOM), and AES, dominate gas accounting for 26%, 23%, and 12% of the capacity, on average, during the same 10-year window.

A.3 Endogenous State Variables

In Figure A1, we first show time-series plots of coal and gas capacity in panels (a) and (b). Given the absence in investment, coal capacity exhibits no variation with AEP accounting for about 1/3 of the approximately 52,000 MW of coal-fired capacity, followed by First Energy and Genon, each accounting for around 15%. Dominion accounts for 10%, while the share of the remaining firms is below 10%. In the case of gas, Dominion, PSEG, AEP, and Duke (DUK) control most of the capacity despite the lack of investment. Genon invests for the first time in 2013 and then again in 2056. PPL also invests in 2013 for the first time and then again in 2050. AES, Exelon (EXE), First Energy, and NRG invest at various points in time during the 50-year period and their combined share of gas capacity increases from 24% in 2013 to 35% in 2062.

Due to lack of investment, there is no improvement in the heat rate of coal-fired capacity, with NRG and PSEG being clear outliers with heat rates exceeding 11.5 MMBtu/MWh (panel (c)). Both heat rates are almost 15% higher than the lowest heat rate of 10.1 that we see for First Energy and PPL. In the case of gas, as expected, we see no improvement in heat rates for AEP, Dominion, Duke, and PSEG due to lack of investment (panel (d)). The firms that invest, however, enjoy a significant improvement in their heat rates.

In Figure A2, we first provide the time-series plots of coal and gas generation in panels (a) and (b), respectively. Dominion, one of the two firms with the largest amounts of gas-fired generation, after experiencing a decrease of 25 million MWh between 2013 and 2032, recovered reaching 49 million MWh by 2062. For PSEG, which is the next largest player in gas-fired generation, the recovery after the significant decrease of 14 million MWh early in the sample, the recovery is not as strong as that for Dominion. The remaining firms all generally experience an increase in gas-fired generation. Duke barely had any gas-fired generation up until 2030, but it reaches 25 million MWh by 2062.

AEP is leading coal-fired generation with more than 100 million MWh of coal-fired capacity in every year between 2014 and 2062 reaching 140 million MWh by the end of the

50-year window. Genon, the second largest player in coal-fired generation, experiences a significant increase in coal-fired generation from 16 million MWh in 2013 to 60 million MWh in 2062. We also see an increase in coal-fired generation for Dominion, Duke, and PPL.

Duke enjoys the highest profits among all strategic firms during the entire 50-year period in panel (c). Duke also enjoys the lowest costs followed by Dominion with the remaining firms experiencing higher costs during the entire period. In the case of Duke, low costs explain the large profits. AEP's large profits are driven by its large volume of coal-fired generation, while those for Dominion by its large volume of gas-fired generation.

A.4 Investment Cost Estimation

First Stage

For the first-stage investment policy functions, we use the (S,s) model, which was originally introduced in the study of inventories and has received attention in the durable-consumption (e.g., Attanasio (2000), Eberly (1994)) and investment literature (e.g., Caballero and Engel (1999) and Ryan (2012)). Fixed costs and empirical evidence suggest lumpy investment behavior in electricity markets; periods of inactivity are followed by notable changes in capacity.

The (S,s) model can accommodate such firm behavior via a target equation, $T(\cdot)$, and a band equation, $B(\cdot)$. The former dictates the level of capacity the firm adjusts to conditional on making a change. The latter dictates when the firm will make a change to its current level of capacity. Using K_{jt} to denote the capacity level for firm j at time t, the policy function for the incumbents is given by:

$$K_{jt+1} = \begin{cases} K_{jt}, & T(K_{jt}) - B(K_{jt}) < K_{jt} < T(K_{jt}) + B(K_{jt}) \\ T(K_{jt}), & \text{otherwise.} \end{cases} \tag{A1}$$

Entrants are assumed to adjust to $T(K_{jt})$. The specification of the target equations resemble those in Fowlie et al. (2016):

$$T(K_{jt}) = \lambda_1^T \mathbf{1}_{[entrant],jt} + \lambda_2^T K_{jt} + \lambda_3^T \mathbf{K}_{-jt} + \lambda_4^T \mathbf{P}_t + \varepsilon_{jt}^T. \tag{A2}$$

In terms of notation, $\mathbf{K}_{-jt}$ is the rivals' capacity and $\mathbf{1}_{[entrant],jt}$ is a dummy variable that equals one if firm j enters the market at time t, and zero otherwise. The vector $\mathbf{P}_t$ includes fuel costs and emissions permit prices.[41] Finally, the idiosyncratic errors is ε_{jt}^T.

In the case of the band, we set it equal to 10% of existing capacity. The implication

[41] Permit prices for SO_2 and NO_x were non-zero during the period 2003–2012 used for estimation.

is that there is no adjustment to capacity in the next period if the target level is within that range. We tried different values, but the investment cost parameters do not seem to be sensitive to that threshold.

Policy Equations Results

Table 6 provides the estimates of the target policy equations. In order to increase the sample and have enough variation in the data, we estimate the target equations for both coal and gas using annual operator-level data for 2003–2012 including all operators and not just those associated with the 10 strategic holding companies in Table 4. Based on the R^2 values reported at the bottom of the table, the fit is better for gas (0.67) than for coal (0.46).

Moving to the regression estimates, the coefficient for the entry dummy is positive and significant at the 1% level in both equations. The target capacity is strongly affected by the current capacity—the associated coefficient is significant at 1% for both fuels. Although the capacity of the rivals has the expected negative sign, it is not significant for both coal and gas. The price of coal has a negative effect on the coal target capacity that is significant at the 5% level, while the price of gas has a positive effect that is significant at the 10% level. The prices of the two fuels have no significant effect on the gas target capacity. The SO_2 and seasonal NO_x permit prices have negative effects on coal target capacity that are significant at the 5% and 10% levels, respectively. The SO_2 permit price has a negative effect on the gas target capacity that is significant at the 10% level. The seasonal NO_x permit price has no effect on the gas target capacity.

Second Stage

Firms have perfect foresight over the future path of the exogenous state variables. This can be seen as a particular form of a Markov process if the state vector does not have the same values at two different points in the future. With the estimates of the policy equations in hand and evolution paths for the exogenous state variables, we estimate the set of structural cost parameters θ for which the observed policy for firm i is the best response to its rivals' observed policies. We begin by estimating the firms' value function using forward simulation and considering the following two cases. In the first case, all firms follow the observed policy, from which the "true" value function will emerge. In the second case, all firms except for firm j follow the observed policies and firm j follows a slightly modified version of its observed policy.

Denote L alternative policies as $\{\sigma_j^l\}_{l=1}^L$ and the observed policy as σ_j^0. For the lth alternative policy, we simulate each firm's decisions over N_T periods using the policy and transition functions from Stage I, and compute the object:

$$\widehat{\mathbf{W}}_j(\mathbf{s};\sigma_j^l,\boldsymbol{\sigma}_{-j}^0) = \sum_{t=1}^{N_T} \beta^t \left(\overline{\pi}_{jt}^l(\mathbf{a}_t,\mathbf{s}_t) - \Gamma_{jt}^l((\mathbf{a}_t,\nu_{jt}))\right). \tag{A3}$$

We then rewrite the MPNE condition (17) for the lth alternative policy as:

$$g_{j,l}(\theta) = \left[\widehat{\mathbf{W}}_j(\mathbf{s};\sigma_j^l,\boldsymbol{\sigma}_{-j}^0) - \widehat{\mathbf{W}}_j(\mathbf{s};\sigma_j^0,\boldsymbol{\sigma}_{-j}^0)\right]\cdot\theta \tag{A4}$$

We draw $L = 20$ alternative policies by adding noise to the optimal policy function. For each of the 10 strategic firms, we perturb the policy function by adding or subtracting 5 MW of generating capacity to the amount resulting from the real policy. We also assume $\beta = 0.90$ and $N_T = 50$ years. We then search for the parameter vector such that profitable deviations from the optimal policies are minimized:

$$\min_\theta \; Q(\theta) = \frac{1}{NL}\sum_{j=1}^{N}\sum_{l=1}^{L} \mathbf{1}\left\{g_{j,l}(\theta) > 0\right\} g_{j,l}(\theta)^2. \tag{A5}$$

We calculate standard errors using 1,000 bootstrap replications by resampling from the moment inequalities and ignoring the 1st stage estimation error as in Bajari et al. (2013).

In what follows, we show that the additive nature of the perturbation is consistent with the heterogeneity assumed for the investment cost function. Noting that we assume linear investment costs and we focus on investment in gas-fired capacity only, the marginal cost of investment exhibits variation across firms and time:

$$\Gamma_{jt} = \gamma_{jt} \times i_{jt}^{ng}, \tag{A6}$$

where $\gamma_{jt} = \overline{\gamma} + \nu_{jt}$ with ν_{jt} being a privately known shock that is IID across firms and time and follows some common distribution defined by its first two moments. Given that firm i does not know the draw of its marginal cost of investment in the beginning of period t when investment decisions are made, the per-period payoff function is given by:

$$\begin{aligned} E_{\nu_{jt}}[\pi_{jt}] = \overline{\pi}_{jt} - E_{\nu_{jt}}\left(\gamma_{jt} i_{jt}^{ng}\right) &= \overline{\pi}_{jt} - E_{\nu_{jt}}(\gamma_{jt}) E_{\nu_{jt}}\left(i_{jt}^{ng}\right) - Cov\left(\gamma_{jt}, i_{jt}^{ng}\right) \\ &= \overline{\pi}_{jt} - \overline{\gamma} E_{\nu_{jt}}\left(i_{jt}^{ng}\right) - Cov\left(\gamma_{jt}, i_{jt}^{ng}\right) \end{aligned} \tag{A7}$$

For estimation, we consider additive positive and negative perturbations of the form $\widetilde{i}_{jt}^{ng} = i_{jt}^{ng} + \chi$, where χ is a constant that is positive for the former and negative for the latter, such that the implied perturbed value function for firm j is given by:

$$\begin{aligned} E_{\nu_{jt}}\left[\widetilde{\pi}_{jt}\right] &= \overline{\pi}_{jt} - \overline{\gamma} E_{\nu_{jt}}\left(\widetilde{i}_{jt}^{ng}\right) - Cov\left(\gamma_{jt}, \widetilde{i}_{jt}^{ng}\right) \\ &= \overline{\pi}_{jt} - \overline{\gamma}\left(E_{\nu_{jt}}\left(i_{jt}^{ng}\right) + \chi\right) - Cov\left(\gamma_{jt}, i_{jt}^{ng}\right). \end{aligned} \tag{A8}$$

The last equality follows from the fact that $Cov\left(\gamma_{jt}, i_{jt}^{ng} + \chi\right) = Cov\left(\gamma_{jt}, i_{jt}^{ng}\right)$. Importantly, the moment condition, which will use the average difference between the value function based on (A7) and the value function based on (A8) across perturbations, is not a function of the covariance term as it cancels out once we calculate the difference. Therefore, the additive perturbations allow us to infer the first moment of the heterogeneity in investment costs but not the second.

A.5 Computational Details for the Counterfactuals

For the purpose of discussion, we focus on the vector of cumulative BAT capacities of each firm in describing our state space.[42] Guided by our estimates, we assume that the strategic firms invest only in gas-fired capacity. Moreover, we only allow positive amounts of investment (no divestment) and assume that capacity does not depreciate. These assumptions are reasonable if we think unused plants just remain idle, and that capacity is long-lived. With these assumptions, we have that BAT capacity either increases or stays at its current level. Finally, we assume that total BAT capacity across firms must be less than or equal 60,000 MW, which, if fully utilized, represents about 60% of total output.

We discretize the state space into a grid with 50 MW increments. Thus in the two player case, our state space has $1201^2 = 1,442,401$ points. We find that interpolating the BAT capacity dimension over a small number of nodes does not capture well enough investment behavior because the interpolation is too smooth relative to the step cost function.

The investment problem is non-stationary because prices, demand, new investment heat rates, and CO_2 targets change each year. To solve the model, we fix all exogenous variables at their 2030 levels post 2030, and solve the associated stationary infinite-horizon problem. This is motivated by the fact that we do not have published CPP targets beyond 2030. Once we have the value functions for 2030, we proceed backwards, starting in 2029 and ending in 2013, noting that the exogenous variables change every year.

Computation for the equilibrium can be divided into two parts: (i) compute stage game

[42] The state vector technically includes the exogenous variables discussed in Section 4.2 and also weighted-average heat rate of each firm's cumulative BAT capacity. For the BAT heat rate dimension of the state space, we use three nodes corresponding to the minimum, average, and maximum heat rates for 2013–2030. We create a dense grid for the state along the BAT heat rate dimension using a cubic spline.

profits for each firm, point in the state space, and year (2014-2029 and the infinite horizon beginning 2030) which require simultaneous clearing of twelve markets (eleven CO_2 and one electricity), and (ii) given stage game profits, solve for the Markov Perfect Nash Equilibrium (MPNE), i.e. a set of investment policy and value functions for each firm, point in the state space, and year. With a discretized state space, we can do the first part separately and also exploit parallel computing to solve for the stage game equilibrium for 24,520,817 ($= 1201^2$ points $\times$ 17 years) points. For the second part we tried standard value function iteration approaches, including the parametric approximation method in Ryan (2012) and Fowlie et al. (2016), but we could not make our solver converge even with lax tolerance, e.g. 10^{-5}. Thus we follow a different approach described below.

We first discuss the algorithm to compute the stage game market equilibrium in Section A.5.1 followed by a discussion of how we solve for the MPNE in Section A.5.2.

A.5.1 Stage Game Market Equilibrium

With regional CPP implementation, two markets have to clear simultaneously: (i) the wholesale market for electricity and (ii) the region-wide CO_2 market. The need to look for a joint solution to both markets arises due to the complementary nature of electricity output and CO_2 emissions. A change in the CO_2 price affects the relative cost of the different fuels. This in turn changes the relative position of each plant in the merit order of the aggregate electricity supply and, therefore, impacts the equilibrium in that market. With state-by-state CPP implementation, there are 11 CO_2 markets and 11 different CO_2 prices. We now have to clear these 11 markets together with the PJM wholesale market simultaneously.

Let q_{ist} denote the electricity output of source i located in state s at time t. In addition, HR_{ist} is the associated heat rate and r_{ist} is the CO_2 emission rate. The mass-based target of CO_2 emissions for state s is $\overline{E}_{st}$. Finally, let S denote the set of the 11 PJM states.

With regional implementation, the equilibrium carbon price is the solution to the following problem:

$$P_t^C = \min\{P : \sum_{s \in S} \sum_{i \in s} (q_{ist}(P) \times HR_{ist} \times r_{ist}) \leq \sum_s \overline{E}_{st}\}. \tag{A9}$$

With state-by-state implementation, the solution is given by the following vector of CO_2 prices:

$$\mathbf{P}_t^C = \min\{\mathbf{P} : \sum_{i \in s} (q_{ist}(\mathbf{P}) \times HR_{ist} \times r_{ist}) \leq \overline{E}_{st}\} \quad \forall s \in S. \tag{A10}$$

With state-by state implementation, the algorithm to solve the minimization problem is the following:

- **Step 1:** start with zero CO_2 prices for all states and compute the PJM wholesale market equilibrium.

- **Step 2:** If at least one state has excess emissions, proceed to Step 3; otherwise, end.

- **Step 3:** Increase the CO_2 price of the state that has the most excess emissions by $1 per short ton.

- **Step 4:** Compute PJM wholesale equilibrium and check for excess emissions.

With regional implementation, we treat the entire PJM area as a single state and the algorithm works in the same way.

A.5.2 Solving for the Markov Perfect Nash Equilibrium

To discuss how we compute the Markov Perfect Nash Equilibrium for our counterfactual analysis, consider a simplified state space where $K_1 + K_2 \leq 2$ and players can invest in unit increments. Figure A4 illustrates the example.

Our approach is reminiscent of the Upwind Gauss-Seidel approach in dynamic programming (Judd, 1998). We first start at the "edge" of the state space and then work backwards as shown in panel (a). The points on the edge are absorbing states hence the values at these points have the form $\pi_i(K_1, K_2)/(1-\beta)$ where $\pi_i(\cdot)$ is the stage game payoff at the given state and β is the common discount factor. Given these values, we can then move backwards to the point $(1, 0)$.

As shown in panel (b), at $(1, 0)$, we can either transition to $(1, 0)$ (no investment), $(2, 0)$ (only player 1 invests) and $(1, 1)$ (only player 2 invests). Since an MPNE is a set of policies and values such that these form a Nash Equilibrium (NE) at the subgame defined by the state, the transition from (1,0) is determined by the pure-strategy NE of the normal form game with payoff matrix given in panel (c).[43] This is the statewise Nash approach implemented in Chen et al. (2009) (see also Doraszelski and Escobar (2010) and Abito et al. (2019)). The payoffs $V_i(2, 0)$ and $V_i(1, 1)$ were already computed from the previous step. The payoff $V_i(1, 0)$ is just $\pi_i(1, 0) + \beta V_i(1, 0) = \pi_i(1, 0)/(1-\beta)$. The payoff $V_i(2, 1)$ is technically undefined since this is outside of our state space. To handle the indeterminacy and at the same time, guarantee existence and uniqueness, we consider a sequential version of this normal form game where player 1 first decides on x_1 followed by player 2. See Bresnahan and Reiss (1990) Berry

[43] We find that it is more straightforward to solve for the Nash Equilibrium in a complete information version of the normal form game and hence we set the privately-observed cost shocks to be equal to zero in the counterfactuals.

(1992) for early examples in static entry game setting, and, more recently, Abbring and Campbell (2010) in an infinite-horizon setting.

A.6 New Source Complements

In the context of the Clean Power Plan, states can voluntarily include emissions from new capacity in their CO_2 targets to address leakage. To accommodate new capacity in the CO_2 targets, the EPA provides an additional emissions budget, the New Source Complements (NSCs) to Mass Goals under Section 111(d) of the Clean Air Act, which implies an upward adjustment to the targets.[44]

To understand the implications of policies to address leakage, we simulate a single-firm optimal investment scenario by taking the equilibrium CO_2 prices from the scenario with industry-profit maximizing and a single CO_2 market (1F-SIN), but not exempting emissions from BAT capacity from CO_2 prices. Given that this approach is equivalent to adjusting the CO_2 targets, we use the term NSC to refer to this scenario.

Our results point to an alarming unintended consequence of policies like the NSCs that are based on *projected* demand growth—that is, on *anticipated* investment—and not on *actual* investment. As Adair and Hoppock (2015) point out, if firms do not invest in new capacity *ex post*, the NSCs effectively reduce the stringency of the regulation by increasing the emissions budget. In fact, we find that under the NSC, firms *do not* invest. An important issue arises due to a one-sided commitment problem: the regulators commit to targets that accommodate new capacity without firms' commitment to build this new capacity. Once the new targets are set and fixed, incentives to invest decrease and it is in the firms' interest not to invest in the first place.

More generally, the one-sided commitment problem provides a rationale for the differential regulatory treatment of new capacity relative to existing capacity, as embedded in the design of the Clean Air Act (Sections 111(b) and (d)). To solve the commitment problem, the regulator has to condition the additional emissions budget allocation on investment actually materializing and this new capacity being used. But this means that there will be a separate accounting of emissions from new sources versus from existing ones, which would necessitate different CO_2 prices for new and existing sources.

[44]The EPA has developed a methodology for quantifying these NSCs that may be summarized as follows. The EPA first calculates the incremental generation needed for each interconnection (Eastern, Western, Texas) to satisfy projected growth in demand from 2012 levels. Following a series of adjustments, the EPA apportions the remaining incremental generation to states on the basis of each state's 2012 share of the interconnection's total generation. Finally, the EPA converts state-level generation to state-level emissions using a predetermined rate (lbs/MWh). For a more detailed discussion of the NSCs, we refer the interested reader to the Technical Support Documentation `https://www.epa.gov/sites/production/files/2015-11/documents/tsd-cpp-new-source-complements.pdf`.

Table A1: Number of plants and units by firm type

year	plants		coal units		gas units	
	non-strategic	strategic	non-strategic	strategic	non-strategic	strategic
2003	73	47	53	55	109	107
2004	108	95	96	142	186	170
2005	149	107	138	160	265	186
2006	133	118	109	182	236	215
2007	118	107	71	149	229	229
2008	119	113	71	150	229	255
2009	119	114	70	153	231	262
2010	130	107	86	133	252	265
2011	139	114	81	153	300	251
2012	156	109	85	135	334	262

Table A2: Capacity and generation by firm type

	all firms				strategic firms			
year	capacity		generation		capacity		generation	
	coal	gas	coal	gas	coal %	gas %	coal %	gas %
2003	26.03	16.43	157.50	13.76	76.74	60.04	77.91	41.83
2004	59.56	33.79	363.49	29.47	80.20	52.33	81.10	54.11
2005	67.85	38.27	421.99	39.42	76.98	48.72	79.01	36.48
2006	67.75	39.67	418.96	41.38	85.10	56.48	86.56	42.59
2007	55.63	42.43	357.58	51.40	89.30	54.46	88.83	52.54
2008	55.53	43.92	343.44	49.22	90.16	55.89	90.11	51.15
2009	56.80	45.68	293.38	62.42	90.34	56.74	90.58	51.76
2010	49.06	48.24	262.59	85.96	86.42	55.11	87.61	52.81
2011	57.06	51.94	284.40	106.89	88.04	48.84	90.40	48.67
2012	60.19	55.34	274.60	146.71	85.48	50.19	87.25	50.88

Note: capacity in thousand MW and generation in million MWh. The 4 rightmost columns of the table show the percentage of capacity and generation by fuel type that strategic firms account for. For example, strategic firms account for 76.74% of coal capacity and 60.04% of gas generation in 2003.

Table A3: Summary statistics for strategic firms

firm	obs	units	cost		fuel price		VOM		heat rate	
			mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
AEP	468	39	42.63	15.51	2.88	0.08	14.61	14.15	10.17	0.55
AES	168	14	36.12	3.26	3.34	0.08	10.27	1.67	10.16	0.89
DOM	276	23	68.10	22.67	3.58	0.17	35.33	18.29	10.22	0.39
DUK	108	9	51.16	1.06	2.52	0.11	26.30	0.00	10.36	0.23
FE	168	14	55.72	32.30	2.96	0.08	32.61	31.29	10.08	0.20
GEN	216	18	56.15	19.92	2.90	0.10	26.78	20.93	10.04	0.51
NRG	108	9	68.69	6.20	3.59	0.64	34.10	4.97	11.20	0.36
PPL	72	6	43.30	1.45	3.60	0.30	12.25	0.50	10.08	0.07
PSE	36	3	62.96	6.52	4.05	0.30	17.22	0.39	11.69	0.03
ALL	1620	135	50.03	22.28	3.04	0.34	22.68	21.33	10.16	0.49

(a) coal

firm	obs	units	cost		fuel price		VOM		heat rate	
			mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
AEP	300	25	33.04	12.30	3.30	0.49	10.06	10.75	7.50	0.87
AES	180	15	78.83	37.66	5.18	1.51	11.82	0.00	13.00	0.47
DOM	576	48	49.09	25.48	4.07	0.75	19.83	21.77	8.14	1.45
DUK	264	22	49.93	7.28	2.91	0.52	30.88	0.00	7.36	0.53
EXE	96	8	69.07	7.15	4.11	0.49	9.65	0.00	14.45	0.00
FE	300	25	32.41	10.69	3.84	0.42	9.68	0.99	7.60	1.39
GEN	240	20	33.13	7.98	3.84	0.65	9.64	0.09	7.41	1.17
NRG	264	22	65.44	20.73	3.56	0.61	8.79	0.19	13.40	1.54
PPL	168	14	40.86	10.07	3.15	0.49	12.62	3.49	9.08	2.21
PSE	756	63	33.70	8.08	3.82	0.78	5.15	1.66	7.86	1.09
ALL	3144	262	40.19	15.73	3.55	0.78	14.77	14.03	7.81	1.28

(a) gas

Note: Cost refers to all-inclusive costs of producing 1 MWh of electricity ($/MWh). The fuel prices are in $/MMBtu. The variable operations-and-maintenance (VOM) costs are in $/MWh. The heat rate is in MMBtu/MWh. The mean and standard deviations reported are weighted by generation. The statistics reported are based on data for the 10 strategic firms listed in the leftmost column. An observation is an electric generating unit by month-of-sample combination in 2012. The full names of the firms listed in the leftmost column are available in Table 4.

Table A4: Capacity of strategic firms (MW, thousands)

firm	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
AEP	0.000	15.583	15.299	15.299	20.096	20.096	20.096	11.669	20.096	19.439
AES	0.378	3.899	3.899	3.899	3.664	3.664	3.664	3.893	3.893	3.893
DOM	0.000	5.504	5.504	5.504	5.575	5.575	5.575	5.495	5.495	6.163
DUK	0.000	0.000	0.000	4.025	0.000	0.000	0.000	0.000	0.000	3.810
EXE	0.895	0.895	0.895	0.895	0.895	0.895	0.895	0.895	0.354	0.000
FE	7.462	12.635	17.781	17.781	9.901	9.901	9.901	9.901	9.901	9.340
GEN	3.198	3.712	3.719	9.353	8.321	8.906	9.672	8.558	9.938	8.648
NRG	5.022	5.022	5.040	1.296	1.278	1.278	1.278	1.278	1.278	1.278
PPL	3.513	3.513	3.496	3.496	3.183	3.183	3.200	3.200	3.200	3.200
PSE	1.313	1.313	1.313	1.313	1.313	1.313	1.313	1.313	1.313	1.313
ALL	21.780	52.075	56.945	62.860	54.226	54.811	55.594	46.202	55.467	57.084

(a) coal

firm	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
AEP	0.000	0.000	1.700	1.700	3.237	3.237	3.237	3.237	3.237	3.915
AES	1.744	3.354	3.354	3.336	2.539	2.572	2.572	2.572	1.606	0.828
DOM	0.000	5.179	4.873	4.873	5.749	6.106	6.285	6.285	6.844	6.844
DUK	0.000	0.000	0.000	3.889	2.737	0.000	2.737	3.462	3.462	3.578
EXE	0.230	0.000	0.000	0.000	0.407	0.407	0.407	0.407	0.407	0.407
FE	1.355	1.756	2.225	2.552	1.825	1.852	1.834	1.834	1.834	1.719
GEN	0.876	0.326	0.326	1.564	1.919	1.919	2.839	2.839	2.839	2.839
NRG	0.087	0.060	0.144	0.100	0.000	0.841	0.951	0.951	0.951	0.951
PPL	0.000	0.000	0.000	0.000	0.550	0.644	0.644	0.639	0.099	2.577
PSE	4.786	5.445	4.524	5.710	5.710	5.710	5.710	5.710	5.255	5.574
ALL	9.077	16.121	17.146	23.724	24.672	23.286	27.214	27.934	26.532	29.232

(b) gas

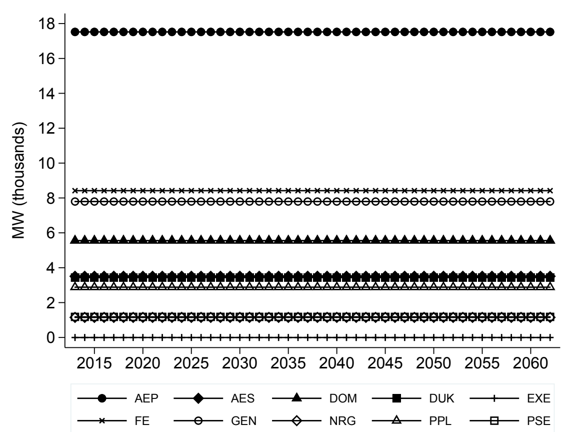
Note: The full names of the firms listed in the leftmost column are available in Table 4.

Table A5: PJM Real-Time Energy Market

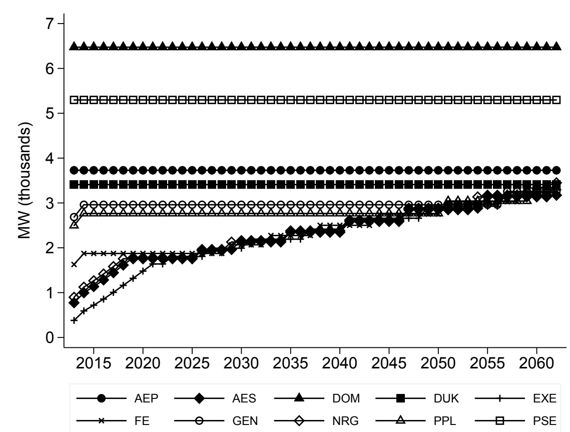
year	price	load	value
2003	$41.23	37,395	$13,506,131,646
2004	$44.34	49,963	$19,406,548,519
2005	$63.46	78,150	$43,444,335,240
2006	$53.35	79,471	$37,140,453,966
2007	$61.66	81,681	$44,119,306,030
2008	$71.13	79,515	$49,545,701,082
2009	$39.05	76,034	$26,009,558,652
2010	$48.35	79,611	$33,718,920,606
2011	$45.94	82,546	$33,219,349,982
2012	$35.23	87,011	$26,852,882,363

Note: The PJM real-time average hourly load (MWh) is from Table 2-30 of the PJM State of the Market Report 2012 available at http://www.monitoringanalytics.com/reports/PJM_State_of_the_Market/2018.shtml. The PJM real-time load-weighted average locational marginal price (LMP) is from Table 2-38 of the same report. The entries in the rightmost column are based on the authors' calculation using value=8760×price×load.

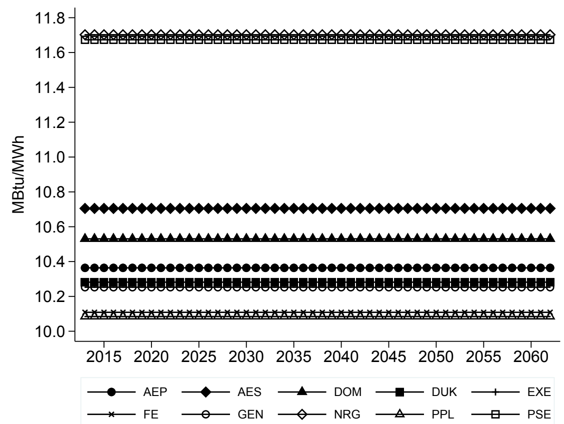
Figure A1: Paths of endogenous variables II, 2013–2062



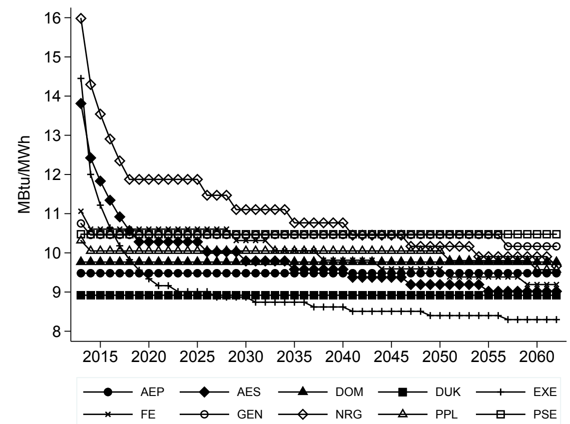
(a) coal capacity



(b) gas capacity



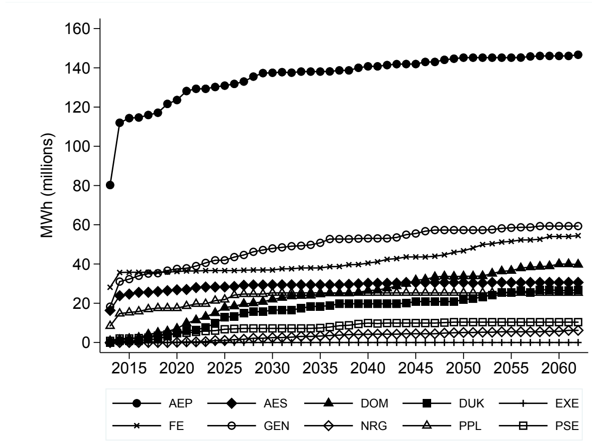
(c) coal heat rate



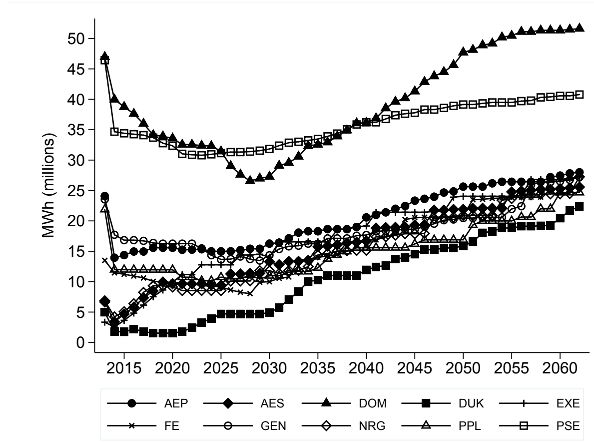
(d) gas heat rate

Note: The heat rates are weighted averages using capacity as weight. The full names of the firms listed in the leftmost column are available in Table 4.

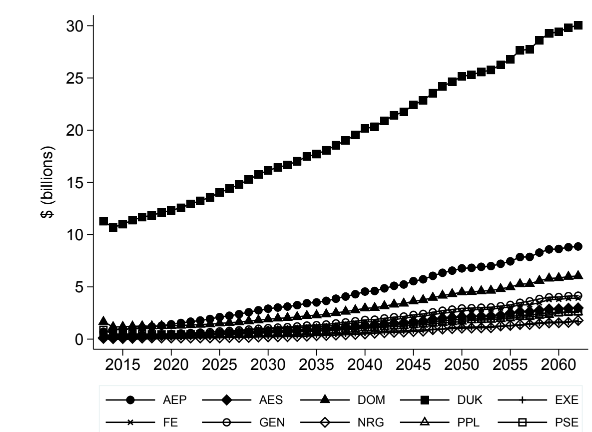
Figure A2: Paths of endogenous variables III, 2013–2062



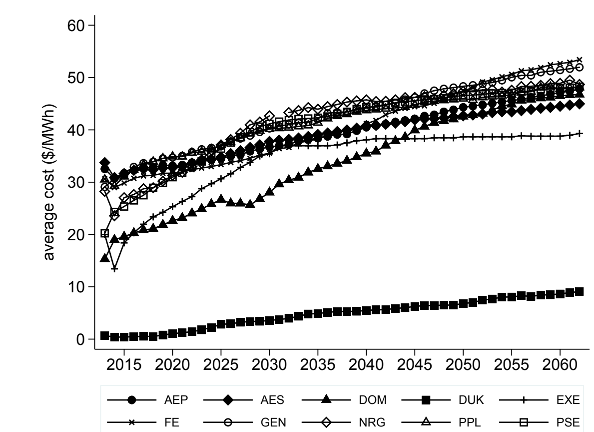
(a) coal generation



(b) gas generation



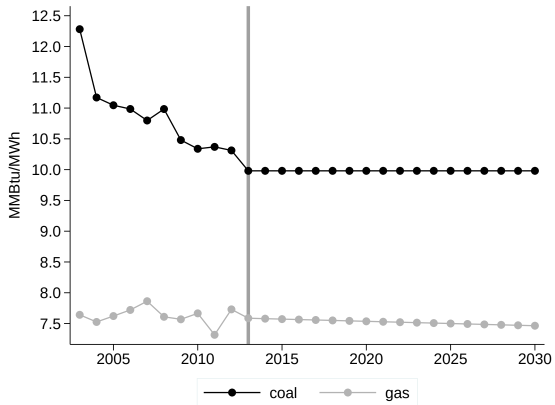
(c) profit from electricity sales



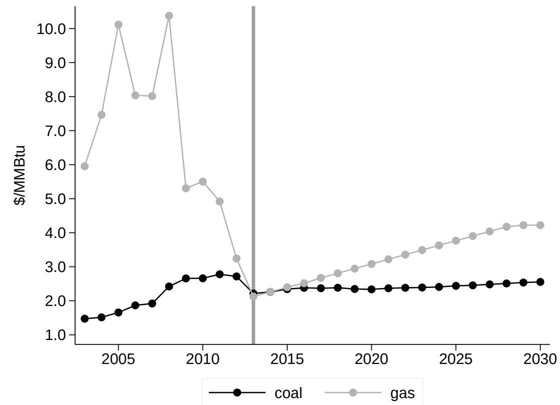
(d) cost of electricity

Note: The profit from electricity sales exclude investment costs. The full names of the firms listed in the leftmost column are available in Table 4.

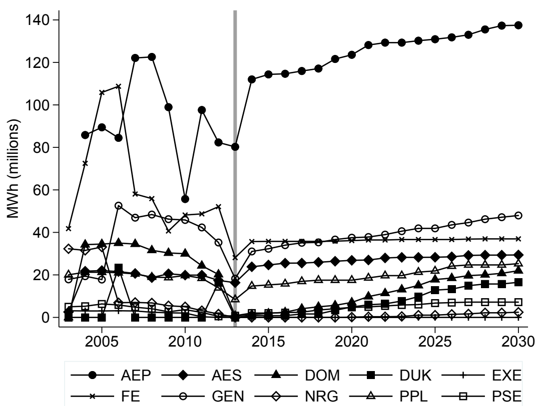
Figure A3: Data and model predictions, 2003–2030



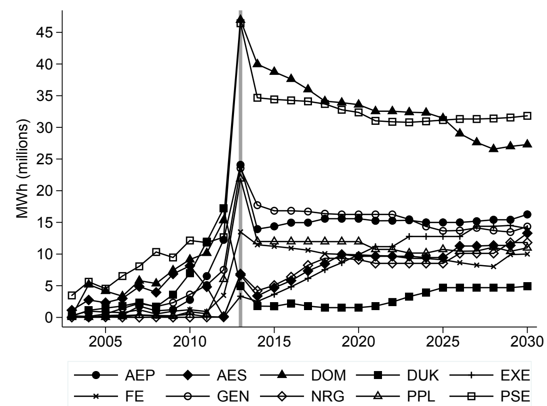
(a) BAT heat rates



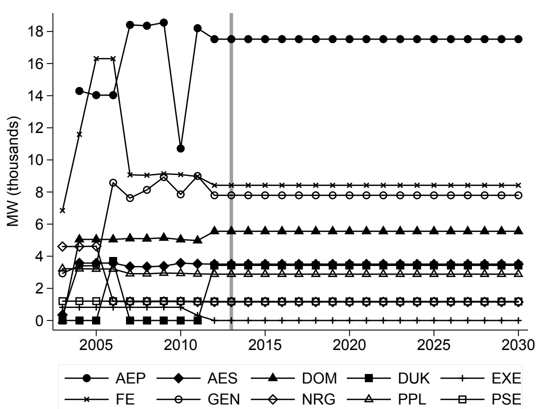
(b) fuel prices



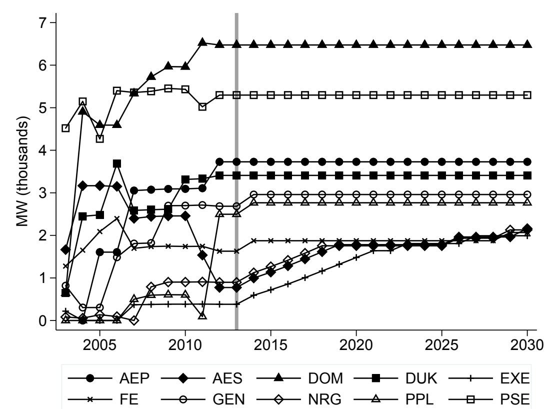
(c) coal generation



(d) gas generation



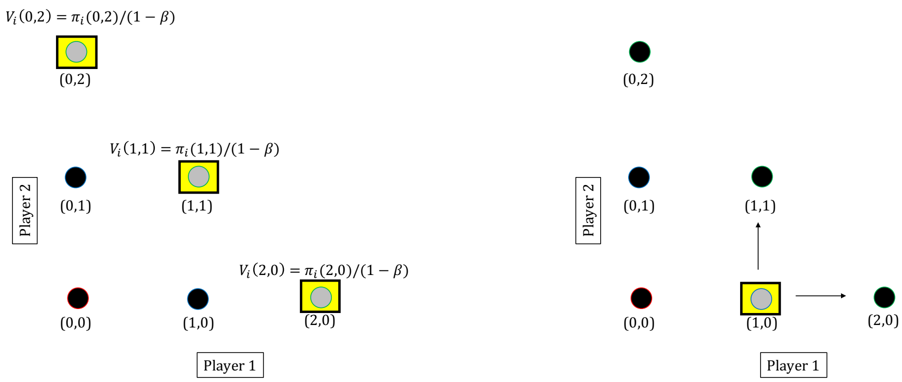
(e) coal capacity



(f) gas capacity

Note: The vertical line indicates the first year of model predictions (2013). BAT refers to best available technology. The full names of the firms listed in the leftmost column are available in Table 4.

Figure A4: Computing MPNE: Simplified Example



(a) Values at absorbing states (b) Possible transitions at $(K_1, K_2) = (1, 0)$

(K_1, K_2)	$x_1 = 0$	$x_1 = 1$
$x_2 = 0$	$V_1(1,0), V_2(1,0)$	$V_1(2,0), V_2(2,0)$
$x_2 = 1$	$V_1(1,1), V_2(1,1)$	$V_1(2,1), V_2(2,1)$

(c) Payoff matrix at $(K_1, K_2) = (1, 0)$

Note: To illustrate how we compute the Markov Perfect Nash Equilibrium for our counterfactual analysis, consider a simplified state space where $K_1 + K_2 \leq 2$ and players can invest in unit increments. We first start at the "edge" of the state space and then work backwards as shown in panel (a). The points on the edge are absorbing states hence the values at these points have the form $\pi_i(K_1, K_2)/(1-\beta)$ where $\pi_i(\cdot)$ is the stage game payoff at the given state and β is the common discount factor. Given these values, we can then consider the point $(1, 0)$. At $(1, 0)$, we can either transition to $(1, 0)$ (no investment), $(2, 0)$ (only player 1 invests) and $(1, 1)$ (only player 2 invests), as in panel (b). The transition is determined by the pure-strategy Nash Equilibrium of the normal form game with payoff matrix given in panel (c). Note that $V_i(2, 1)$ is technically undefined since this is outside of our state space. Moreover, existence and uniqueness of the pure-strategy NE is not guaranteed. Thus we instead consider a sequential version of this normal form game where player 1 first decides on x_1 followed by player 2. This solves the existence and uniqueness problem, and also the indeterminacy of $V_i(2, 1)$ (i.e. $V_i(2, 1) = V_i(2, 0)$).