The Role of Output Reallocation and Investment in Incomplete Environmental Regulation

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Abstract

Inefficiencies from uncoordinated regulation of a negative environmental externality are significantly mitigated when firms participate in an integrated product market. Firms take into account the distribution of externality prices and reallocate output from high to low externality-priced areas, triggering price readjustment, and potentially price convergence. When capacity constraints prevent reallocation, the marginal benefit of investing in new—often more efficient and cleaner capacity—increases, which can be welfare-enhancing. To quantify these effects, we estimate a dynamic structural model of supply and investment using data from a large U.S. wholesale electricity market, and simulate the model under counterfactual CO_2 emissions regulations.

Keywords: Incomplete Regulation, Emissions Markets, Market Structure, Strategic Investment, Empirical Games.

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

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1 Introduction

Economists have long advocated for market-based solutions to correct environmental externalities such as harmful emissions from combustion of fossil fuels. Although a single, unified market for the externality is ideal to maximize gains from trade among heterogeneous polluting sources, only separate externality markets, at best, may be feasible due to the difficulty of coordinating regulations across jurisdictions. For example, countries *voluntarily* pledge to take actions to mitigate the risks and effects of climate change as part of the Paris Agreement, and each country determines and implements mitigation strategies absent any strict supranational enforcement mechanism. According to The International Carbon Action Partnership, there are 27 jurisdictions currently implementing or are scheduled to implement a form of carbon emissions trading system (ETS). Among these jurisdictions, one is supranational (European Union ETS), four are at the country-level (China, Colombia, New Zealand, Switzerland), fifteen are provinces and states, and seven are cities.[1] Difficulties in coordinating regulation across jurisdictions *within* the same country are in fact usually the first hurdle in any country-level effort to create a single carbon market. In the U.S. for example, attempts to federally address greenhouse gas emissions have largely failed and further attempts on regulations are likely to be at the state level.[2]

Difficulties in organizing a single market to correct an externality raise the question to what extent having uncoordinated regulations is an adequate substitute. The main objective of this paper is to empirically investigate this question and understand the mechanisms that drive their relative efficiencies.

Our paper focuses on regulation of carbon dioxide (CO_2) emissions from power plants that participate in the Pennsylvania-New-Jersey-Maryland (PJM) wholesale electricity market. PJM operates the world's largest wholesale electricity market covering all or parts of 13 states. Between 2005 and 2012, fossil fuels (coal, gas, oil) accounted for about 60% of

[1]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. Not surprisingly, discussions regarding the type of policies that the UK may implement following *Brexit* departure have already started. This is particularly important in light of the fact that, while the UK pledged a 57% reduction in CO_2 emissions in the Paris Agreement, the EU as a whole was less ambitious, proposing only a 40% reduction (Hepburn and Teytelboym (2017)).

[2]There are two reasons why CO_2 regulations are likely to be at the state level. First, on October 10, 2017, the Trump administration submitted a proposal to repeal the U.S. Clean Power Plan (CPP), setting back federal-level efforts to limit CO_2 emissions from electric power plants set forth during the Obama Administration. Second, unless new legislation is passed in congress, regulations will fall under the Clean Air Act (CAA), as in the CPP. Although the CAA is at the federal level, it only authorizes the U.S. Environmental Protection Agency (EPA) to set state-level targets and solicit state implementation plans to achieve these targets.

electricity generation each year, on average. During the same period, close to an average of 322 million metric tons of CO_2 were emitted each year by electric utility plants located in PJM. To put these emissions in a perspective, the whole U.S. electricity generation sector emitted about 2,262 million metric tons.

We estimate a dynamic structural model of production and investment, and use the estimated model to simulate the introductions of a PJM-wide cap or a state-by-state limit on CO_2 emissions to compare welfare in the two regulatory regimes. With state-by-state implementation, emissions in each state cannot exceed their respective state-level targets, hence essentially acting as if there were separate CO_2 markets for each state and inter-state trading is not allowed. In contrast, when states in PJM can pool their targets and comply as a region, only a single constraint needs to be satisfied. Thus, with state-by-state implementation, firms operating power plants across the PJM region face different CO_2 prices depending on which state their plants are located in, while with regional implementation, firms face a single CO_2 price regardless of their plants' location.

The paper has two key insights. First, the organization of the product (electricity) market can effectively coordinate uncoordinated regulation of the negative externality (CO_2 emissions) as long as there is sufficient capacity across different markets. Existing work on externality markets has mainly focused on quantifying the gains from emissions permit trading (e.g., Bui (1998) and Carlson et al. (2000)) and, to our knowledge, has never discussed the role that the product market can play in coordinating regulations across different jurisdictions. Facing an integrated product market, multi-plant firms make output decisions taking into account the distribution of externality (shadow) prices across markets. All else equal, profit-maximizing firms move production from markets with higher externality prices to markets with lower externality prices. As long as there is sufficient capacity across markets, output reallocation and externality price readjustment will lead to convergence of externality prices, as if there were a single externality market. This idea is reminiscent of Samuelson's factor price equalization theorem in that integration of product markets will equalize prices of factors of production despite restrictions on the movement of these factors across countries.[3] Finally, the implicit coordination of environmental regulations via the product market can be seen as a form of *private* regulation in response to the difficulty of coordinating environmental

[3] The coordinating benefits from an integrated electricity market is also relevant for the international trade literature, and, particularly, for recent work regarding the gains from cross-border trade in electricity. For example, Antweiler (2016) discusses the potential gains from electricity trade between Canadian provinces and U.S. states. Because electricity demand is stochastic and correlated across jurisdictions, electric utilities can reduce their cost during peak periods by importing cheaper off-peak electricity from neighboring jurisdictions. We point to an additional benefit of electricity market integration due to the implicit coordination of environmental policies across jurisdictions.

regulations across jurisdictions (Abito et al. (2016)). Unlike markets for externalities—which, by nature, often have to be created and organized by multiple *public* institutions—product markets arise more naturally as a result of demand and supply. Moreover, product markets often extend to multiple jurisdictions because *private* entities are not tied to a specific jurisdiction unlike public agencies.

Second, we show that investment incentives are different with single and separate externality markets and therefore a dynamic analysis (where capacity is endogenous) is needed to have an accurate comparison of welfare. Holding fixed the level of investment with single and separate externality markets, welfare is lower in the latter unless there is sufficient capacity to facilitate reallocation of output and readjustment of externality prices. However, this "static analysis" is misleading since, all else equal, the marginal benefit of investment is higher with separate externality markets compared to a single externality market. Under separate externality markets, new capacity has the added value of allowing firms to reallocate output from high externality priced-markets to low externality-priced markets. This added benefit of investment is not present with a single externality market. Thus, separate externality markets essentially *foment* firms to invest more and reach a higher steady state level of new capacity (Abito et al. (2016)). To the extent that there are existing distortions that lead to under-investment (e.g. strategic capacity withholding and lax environmental regulations), total welfare may actually be higher with separate externality markets than in a single market.

To quantify welfare with single and separate externality markets, we first estimate plant-level marginal costs and investment costs. We rely on data on plant-level efficiency (heat rate), emission rates for various pollutants and associated compliance costs, and other operations-and-maintenance (O&M) costs to estimate marginal cost functions for each plant following Mansur (2007) and Bushnell et al. (2008). To estimate investment costs, we use the two-step approach in Bajari et al. (2007) closely following Ryan (2012) and Fowlie et al. (2016). The two-step method allows us to estimate investment costs without explicitly solving the equilibrium of the model. Our estimates on costs combined with predictions on future fuel prices capture the supply side of our model while predictions on electricity demand in PJM capture the demand side.

We then make the following assumptions in terms of supply and investment behavior. Based on the results regarding PJM in Bushnell et al. (2008), we assume that, conditional on existing capacity at the beginning of each period, the wholesale electricity market is competitive. In contrast, we assume that the ten largest firms in PJM invest in new plants strategically.[4]

[4]Dixon (1985) analyzes a model where the market is competitive but firms can strategically invest. He

That is, these firms take into account their rivals' reactions to their investment decisions, as well as the effect of investment on future market outcomes. On the one hand, investment in new coal- and gas-fired capacity allows firms to produce at lower cost and, potentially, increase profits from electricity sales in subsequent periods. On the other hand, an increase in investment in new capacity may depress electricity prices, leading to lower profits.

Since plants in PJM are not subject to CO_2 regulations,[5] we take the CO_2 emissions targets from the Clean Power Plan (CPP) formulated during the Obama Administration but then essentially repealed under the Trump Administration. The targets are limits to the annual tonnage of CO_2 that power plants in each state can emit acting as a cap on CO_2 emissions. To implement a single externality market, we assume that states can comply by satisfying a PJM-wide CO_2 limit, which is computed by summing up the individual states' targets. We assume that the CPP is in place during 2022–2030 and we simulate production and investment beginning in 2014.

When we set investment to be the same with single and separate externality markets, i.e. "static analysis," we find no difference in welfare if new capacity by 2030 is in excess of 50,000 megawatt (MW) or 50% of output. In this case, there is sufficient capacity to facilitate reallocation of output and readjustment of CO_2 prices across states. As expected, for lower levels of new capacity, welfare is higher under a single externality market. The largest difference in welfare is $0.5 billion, which is about a 0.4% decrease in welfare.

Since investment is treated as exogenous in the static analysis, it ignores a potentially important channel that affects the relative efficiencies between single and separate externality markets. Therefore as a next step, we solve our dynamic model to account for optimal investment. Because investment relaxes capacity constraints that prevent firms to reallocate output, the marginal benefit of investment is higher under separate externality markets. Thus we find that, in general, investment with separate externality markets are higher and occurs earlier than with a single externality market. Finally, when firms invest strategically, welfare with separate externality markets is actually $3.8 to $8.6 billion *higher* than with a single externality market since overall investment is lower than the socially optimal level.

Our paper contributes to several streams of the literature. First, it is related to the literature that investigates the interaction between environmental regulation and other forms of regulation and market structure. Recent papers in this literature include Fowlie (2010)

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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.

[5]There are a couple of exceptions. First Maryland is part of the Regional Greenhouse Gas Initiative which is a cap-and-trade program. New Jersey was initially a member as well but left in 2012. However, New Jersey is scheduled to return in the program in 2020.

on the interaction of the NO_x Budget Program with rate-of-return (RoR) regulation, Abito (2017) on the interaction between the Acid Rain Program and RoR-related 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. Of these papers, the closest are Ryan (2012) and Fowlie et al. (2016) (henceforth, FRR) in terms of methodology. We follow their Markov Perfect Nash equilibrium framework and two-step estimation method, although we depart from their approach in that we do not need to estimate production costs but instead compute these costs directly from the data.

Second, our paper is related to the literature on incomplete regulation, lack of policy coordination, and strategic policy choice. Recent work on incomplete regulation, such as by Fowlie (2009) and FRR, where only a subset of polluting sources are subject to regulation, has emphasized the problem of emissions leakage whereby firms divert production towards unregulated sources. 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)). Although reallocation of output from high CO_2 -priced areas to low CO_2 -priced areas is technically a form of emissions leakage, our analysis allows for CO_2 prices to adjust hence dampening the negative effects of leakage. More recently, Bushnell et al. (2017b) (henceforth, BHHK) study differences in regulatory environment across states resulting from lack of coordination and strategic policy choice. In terms of the institutional setting (Clean Power Plan), the paper by BHHK is closest to ours.[6]

Finally, our paper is related 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)).

The remainder of the paper is organized as follows. Section 2 provides the underlying

[6]BHHK 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 regulations. In contrast, we take a step back from the specific design of the policy, and focus on the question of single (coordinated) versus separate (uncoordinated) markets, how an integrated product market allows implicit coordination of uncoordinated policies and quantifying the role of investment.

economic intuition of the paper while Section 3 gives some background on our empirical setting. We present our empirical model in Section 4, followed by a discussion of estimation and empirical results in Section 5. Section 6 is devoted to the simulations of alternative investment scenarios for our welfare analysis. We finally conclude. In the online Appendix, we present a simple model of CO_2 regulation highlighting the role of optimal reallocation of production and investment as mechanisms that allow coordination in the presence of multiple markets for an externality. Additional details regarding the data, our empirical analysis, the heterogeneity of investment costs in our model, and the emissions' market clearing algorithm are also delegated to the Appendix.

2 Intuition

In this section, we discuss the key economic forces that affect the gap in welfare between a single and separate externality markets. Our analysis starts with assuming capacities are fixed, and focuses on the ability of an integrated product market to coordinate separate externality markets through reallocation of production across locations. We then move to the case where firms choose investment optimally. We argue that since capacity constraints that restrict reallocation creates an additional incentive to invest, investment tend to be higher with separate externality markets.

Static analysis. The stylized model in the online Appendix shows that as long as there is sufficient capacity across locations, an efficient solution (i.e. where marginal production and abatement costs across locations are equal) can be achieved even with separate externality markets. Intuitively, a firm will reallocate production from locations with high externality (shadow) prices to locations with low externality prices, all else equal. As more (less) output is produced in the location with a low (high) externality price, the amount of the externality in this location goes up (down) hence driving the externality price up (down) as well. Reallocation of output and readjustment of the externality price continue until either prices are equal across locations (hence as if there was a single externality market) or the firm faces a capacity constraint.

When capacity constraints are binding, the marginal abatement costs across locations will not be equal. In this case, total welfare will be higher with a single externality market. Since we are holding capacity fixed in the static analysis, the difference in welfare with a single and separate externality markets is basically the vertical distance between the two curves in panel (a) of Figure 1.

Dynamic analysis. The static model works as a useful benchmark to gauge the efficacy of the reallocation mechanism when capacities are fixed. However, ignoring dynamic considerations can substantially affect our conclusions. The key economic force at play is the firm's greater incentive to invest with separate externality markets.

As we saw in the static analysis, with separate externality markets, differences in externality prices across locations provide an incentive for a firm to reallocate output. Moreover, a firm's ability to reallocate output is determined by its existing capacity. When capacity constraints are binding, the desire to reallocate output creates an additional incentive to invest in new capacity.

The stronger incentive to invest with separate externality markets can have ambiguous effects on welfare as shown in panel (b) of Figure 1. First, on the environmental side, higher investment allows firms to shift production to jurisdictions that are less constrained by the regulation of the externality, hence leading to "too much emissions," i.e. emissions leakage (Fowlie, 2010). On the other hand, since investment is in new capacity, it displaces existing inefficient and dirtier units from locations where the externality price is high. Second, in terms of competitive effects, an increase in capacity counterbalances the incentive to reduce investment for strategic reasons, such as to increase the equilibrium price in the product market (Dixon, 1985). However, there can also be strategic reasons why firms over-invest relative to what is socially optimal.[7] Therefore, whether the private optimal level of investment is higher or lower than the socially optimal level is ultimately an empirical question.

3 Background

3.1 PJM Electricity Market

The Pennsylvania-New Jersey-Maryland (PJM) Interconnection operates the world's largest wholesale electricity market as the regional transmission organization (RTO) for the area that encompasses 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

[7] Over-investment may also arise when firms do not internalize the cost that their capacity additions impose on their rivals, i.e., the Mankiw and Whinston (1986) business stealing effect. Fudenberg and Tirole (1984) provide a taxonomy of various entry deterrence strategies involving both over- and under-investment.

market operator, PJM balances the needs of buyers, sellers and other market participants and monitors market activities to ensure "open, fair and equitable access."[8] 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.[9] 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 (AEP), while all natural gas capacity in North Carolina is owned by Dominion. HHI for capacity in states that have at least two companies ranges from 2209 (Pennsylvania) to 9876 (IN) for coal, and 1786 (Pennsylvania) to 9910 (Kentucky) for natural gas.

Finally, Figure 3 shows that monthly average electricity prices track closely the gas price paid by the power plants in PJM for 2003–2012, which is expected because gas-fired generators usually set the price at which the market clears. During this 10-year window, the gas share of (coal plus gas) generation increased from 6% to 40% in April of 2012 before falling to 29% in December of the same year. Setting aside the seasonality in the share of gas, there is a clear upward trend that is more pronounced beginning in late 2008, which is consistent with the lower natural gas prices the electric power industry experienced nationwide due to the exogenous shift in the supply of gas following the shale boom. PJM sits on the top of prolific shale gas formations (e.g., the Marcellus shale in Pennsylvania) and a very dense network of natural gas pipelines enjoying access to abundant cheap natural gas. Coal prices paid by power plants in PJM, on the other hand, exhibited an upward trend, which is largely consistent with the trend in coal prices for the entire country.

[8] 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.

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

3.2 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 has proposed to repeal (October 7, 2018) and replace (August 21, 2018) the Obama-era rules, 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 which is the Clean Air Act (CAA).

Under 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.[10] 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 CPP also established mass-based state goals with a new source complement representing EPA's estimated new source emissions associated with growth in the demand for electricity relative to its 2012 levels. The EPA gave the states the flexibility to develop and implement plans to ensure that power plants

[10]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, i.e. presumably after 2030.

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.[11]

Table 2 shows the CPP mass-based targets for the 11 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 in 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, which has implications for the policy experiments we consider later in the paper, where we compare market outcomes for the regional and state-by-state implementation of the CPP. 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 across states. Taking 2012 CO_2 emissions as a base, targets require a 50% or more decrease in CO_2 emission in Kentucky (52%), Illinois (52%), Indiana (50%), West Virginia (50%) and Maryland (50%). On the other hand, targets require a less than 50% decrease in CO_2 emissions in Ohio (49%), Pennsylvania (46%), North Carolina (39%), Virginia (30%) and New Jersey (24%).

Given the variation in stringency, we can look at how coal and natural gas capacity of some of the dominant firms are distributed across the region. For example, we can look at what fraction of a firm's combined coal and natural gas capacity is in a state that requires a less

[11] 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.

than 50% CO_2 emissions reduction: First Energy with 52%, AEP with 39%, Dominion with 75%, and Duke with 89%. We can also look at two specific states such as Pennsylvania with a 46% reduction and New Jersey with a 24% reduction. For example, in terms of NRG's combined coal and natural gas capacity, 59% is in Pennsylvania while 41% is in New Jersey.

We end this section with a remark. The separate rules for existing and new plants provide two useful assumptions. First, since 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 in each period, multiple CO_2 markets and the electricity market all have to clear simultaneously. Second, since firms must 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.

4 Model

We now present our model of the PJM wholesale electricity market. Figure 4 provides an overview of the timing of the model. We model the market interaction as a dynamic stochastic game where, in the beginning of each period, firms invest in new plants after which they compete to supply electricity given their current portfolio of plants. Each firm owns a portfolio of plants that can differ in various dimensions such as fuel-type, capacity, efficiency, emissions rate and the state where the plant is located. 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. The rest of the firms belong to the *fringe*. The fringe is exogenously endowed with a portfolio of plants that remain fixed throughout the analysis.

We first describe how we model electricity demand followed by a discussion of firms' supply decisions conditional on the portfolio of plants. We then discuss how plant portfolios endogenously evolve through firm's choice of investment. We close the section with a discussion of the equilibrium concept we adopt in the model.

4.1 Electricity Demand

To model demand, we adapt the approach in Bushnell et al. (2008) (henceforth, BMS) using monthly data but with 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 listed in Table 4, noting that we aggregate subsidiaries to holding companies. This fringe supply consists of the following: (i) net imports, (ii) supply of fringe firms, (iii) supply of strategic firms from sources other than coal and gas. We then estimate the following fringe supply function:

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

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:

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

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

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

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

Finally, we write:

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

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.

4.2 Firms

4.2.1 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.). Note also that we have simplified the notation in (8) to highlight the cross-sectional and time variation of the various cost components. 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. The marginal cost function for each firm is then constructed by ordering the plants from lowest to highest marginal cost. Because we observe all of the components in (8), we can compute each firm's marginal cost directly from the data.

4.2.2 Evolution of Plant Portfolios

A firm's investment affects the shape of the marginal cost function by changing the portfolio of plants that the firm owns and operates. In the beginning of each year, a firm can choose to invest in coal- or gas-fired capacity. Although we do not assume a minimize size of a plant the firm can invest in, we assume that firms can choose capacity of the new plant in 1 MW increments. Aside from the choice of fuel-type and capacity, we also need to determine the heat rate of the plant the firms can invest in. For this we rely on Section 111(b) of the Clean Air Act discussed in Section 3.2 which essentially requires that new capacity have the best available technology (BAT). To implement this assumption in our model, we assume that firms can only invest in plants that have the best heat rate during the investment year.[12]

Aside from simplifying the choice of plant-type a firm can invest in in a given year, the BAT assumption also helps in making our model tractable. In general, we need to take stock of the type of plant a firm invests in each year. Moreover, when a firm is evaluating different investment strategies it can take today, it has to be able to compute future profit flows under different investment scenarios involving different paths its plant portfolio can take.

Figure 5 illustrates how the BAT assumption helps us to address the dimensionality problem. The key idea is that since the firm is investing in a plant that has the best heat rate, this plant is likely to be infra-marginal with respect to the PJM wholesale electricity market, at least in the medium run.[13] The two lower steps of the supply curve in panels (a) and (b) of Figure 5 represent investment in new capacity, while the remaining portion of the supply curve corresponds to existing capacity. Panel (a) shows the wholesale electricity market equilibrium when we keep track of all the information about new capacity that the firm invests in. Panel (b) shows that rearranging infra-marginal units actually does not alter equilibrium quantities, prices, and profits, as long as these units remain infra-marginal. Finally, panel (c) shows that we only need to keep track of an average of all the new capacity that the firm invests in since averaging of these individual units does not affect equilibrium quantities, prices, and profits. Thus, as long as new capacity is infra-marginal, tracking the firm-level cumulative BAT capacity and the associated average heat rate is sufficient for our empirical analysis.

[12] We discuss the evolution of heat rates in Section 5.3.

[13] We loosely define the medium run as a time horizon where plants that existed in 2012 are still supplying positive quantities in equilibrium.

Using $f \in \mathscr{F} = \{coal, gas\}$ to denote the fuel, 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 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 $\underline{K}_{jt}$ with an associated marginal cost 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, the new supply curve, which is a collection of (K_{jt+1}, c_{jt+1}) points, is obtained through a shift of the supply curve at time t. For example, suppose there is only one firm investing in gas, which gives rise to $\underline{K}_{jt}$ with associated cost $\underline{c}_{jt}$, which we assume for illustrative purposes to be less than the marginal cost of all existing capacity.[14] Then the first step of the new supply curve becomes $(\underline{K}_{jt}, \underline{c}_{jt})$. The rest of the supply curve is characterized by $(K_{-jt} + i^{gas}_{jt}, c_{-jt})$, that is a horizontal shift equal to the amount of investment. This example is illustrated in panel (b) of Figure 6.

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 associated with renewable sources in a flexible way through exogenous

[14]Since infra-marginal units can be rearranged, what suffices for the horizontal shifting to maintain the same equilibrium is that new capacity is infra-marginal.

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 (RPS) which we observe in the data and assume to bind at least in the medium run. The RPS mandates that a specific fraction of all electricity generated has to come from renewable sources. With a binding RPS, investment in renewable sources are driven by regulation rather than profit maximization. In our empirical application, we collect information on the RPS future mandates for the different states that comprise the PJM market, which we use in our simulations.

4.3 Equilibrium

4.3.1 Electricity Market Equilibrium

To model firms' supply decision in the wholesale electricity market, we build on the results in Wolak (2000) and Bushnell et al. (2008). 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 those from a perfectly competitive setting than to those from a Cournot game.[15] Therefore, we implement our model as if firms were price-takers producing electricity subject to capacity constraints.[16] The equilibrium wholesale electricity price is then determined by the intersection of supply and demand, where supply is just a "merit" order of all sources in terms of their marginal costs.

Market supply is determined by ordering all available capacity in terms of its marginal costs similar to Figure 6. This merit order along the supply curve 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

[15]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 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. Basically the first approach of assuming exogenous forward contracts is isomorphic to assuming perfectly competitive markets. While interesting, modeling the endogenous evolution of forward commitments is beyond the scope of the paper.

[16]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.

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. Because we observe all of the components in (8), we can construct this step function directly from the data.

Remark. Investment decisions are strategic; 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 consistent with theory.[17] 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.

4.3.2 Markov Perfect Nash Equilibrium

The actions chosen by each firm j are represented by $a_{jt} = \{q_{jt}, i_{jt}^{coal}, i_{jt}^{gas}\}$. The variable q_{jt} denotes the output (electricity generation) by firm j while i_{jt}^{f} is the investment in capacity fired by fuel f. 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.

We assume a state vector

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

The endogenous part of the state vector, $\{\underline{K}_{jt}, \underline{S}_{jt}, \underline{HR}_{jt}^{coal}, \underline{HR}_{jt}^{ng}\}$, relates to BAT capacity investment and its evolution is discussed in the previous subsection. In terms of the exogenous state variables, α_t is the intercept of the inverse residual monthly demand for electricity and $\mathbf{p}_t^f$ 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

[17] See also Dixon (1985) for an equilibrium analysis.

[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 level such as VOM are held constant at the current values and, hence, need not be considered in the state vector.

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

where

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

represents the profit from the wholesale electricity market before investment cost $\Gamma_{jt}(\mathbf{a}_t, \nu_{jt})$. Here, p^r_{jt} represents 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, the function $C(q_{jt}, \mathbf{s}_t)$ denotes the total cost of producing q_{jt} given state $\mathbf{s}_t$.

We assume 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 the superscript f denotes the fuel-type (coal or natural gas) of the plant the firm invests in, ν_{jt} a private shock that is independently distributed across firms and time, and drawn from a common distribution $G_\nu = (0, \sigma^2_\nu)$, and γ^f is an investment parameter that we need to estimate.[19]

We assume 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

[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.

function for firm j given by:

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

Remark. In our model, we assume that all the benefits from investment come from the profits firms earn in the wholesale electricity market. However, a mechanism referred to as capacity auctions exist in PJM, the goal of which is to encourage investment in new capacity. The motivation for capacity auctions is to have adequate resources on the grid to ensure that the demand for electricity can be met at all times in the near future. In PJM's case, a utility or other electricity supplier is required to have the resources to meet its customers' demand plus a reserve. These load serving entities (LSEs) can meet the resource requirement with generating capacity they own, with capacity they purchase from others under contract, through demand response—in which end-use customers reduce their usage in exchange for payment—or with capacity obtained through the capacity auctions themselves.

Since we do not model capacity auctions, one may worry that we are missing capacity payments that incentivize firms to invest. Although we do not explicitly model capacity payments, our approach is robust to their presence. In the presence of capacity payments, Γ_{jt} becomes the investment cost *net of* the expected future value of capacity payments. Of course, this interpretation of capacity payments is valid only when all new investment receives capacity payments. Furthermore, our setup can accommodate heterogeneity in capacity payments because of zonal pricing through the private shock ν_{jt}. It is also important to note that during 2003–2012, capacity payments have accounted for 6% of the total wholesale price per MWh when energy payments accounted for 82%.[20]

[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.

5 Estimation

We estimate our model 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 estimated parameters that are not primitives of the underlying economic model of investment. In the second stage, we search for the structural parameters that best rationalize firms' observed behavior and transitions of the state variables. The advantage of this approach is that the primitives can be estimated without the need to solve for an equilibrium. As it is the case with all two-stage methods, the first-stage estimates do not fully exploit the structure of the dynamic game.

5.1 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:

$$K_{jt+1} = \begin{cases} K_{jt}, & T(K_{jt}) - B(K_{jt}) < K_{jt} < T(K_{jt}) + B(K_{jt}) \\ T(K_{jt}), & \text{otherwise.} \end{cases} \tag{19}$$

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

$$T(K_{jt}) = \lambda_1^T \mathbf{1}_{[entrant],jt} + \lambda_2^T K_{jt} + \lambda_3^T \mathbf{K}_{-jt} + \lambda_4^T \mathbf{P}_t + \varepsilon_{jt}^T \tag{20}$$

$$B(K_{jt}) = \lambda_1^B + \lambda_2^B K_{jt} + \varepsilon_{jt}^B. \tag{21}$$

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.[21] Finally, the idiosyncratic errors are ε^T_{jt} and ε^B_{jt}.

5.2 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 $\mathbf{W}_j(\mathbf{s}; \sigma^l_j, \boldsymbol{\sigma}_{-j})$ 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.

With L alternative policies $\{\sigma^l_j\}^L_{l=1}$ and using σ^0_j to denote the observed policy, we want to estimate $\mathbf{W}_j(\mathbf{s}; \sigma^l_j, \boldsymbol{\sigma}^0_{-j})$ for $l = 1, ...L$. For the lth alternative policy, we simulate each firm's decisions over N_T periods using the policy and transition functions from Stage I, such that the resulting estimator is:

$$\widehat{\mathbf{W}}_j(\mathbf{s}; \sigma^l_j, \boldsymbol{\sigma}^0_{-j}) = \sum_{t=1}^{N_T} \beta^t \left(\overline{\pi}^l_{jt}(\mathbf{a}_t, \mathbf{s}_t) - \Gamma^l_{jt}((\mathbf{a}_t, \nu_{jt}))\right). \tag{22}$$

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

$$g_{j,l}(\theta) = \left[\widehat{\mathbf{W}}_j(\mathbf{s}; \sigma^l_j, \boldsymbol{\sigma}^0_{-j}) - \widehat{\mathbf{W}}_j(\mathbf{s}; \sigma^0_j, \boldsymbol{\sigma}^0_{-j})\right] \cdot \theta \tag{23}$$

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. In Section A.5, we show that the additive nature of the perturbation is consistent with the heterogeneity assumed for the investment cost function. 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

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

minimized:

$$\min_{\theta}\ Q(\theta) = \frac{1}{NL}\sum_{j=1}^{N}\sum_{l=1}^{L}\mathbf{1}\left\{g_{j,l}(\theta) > 0\right\} g_{j,l}(\theta)^2. \tag{24}$$

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).

5.3 Results

Static Estimates. Table 5 contains the estimates for the fringe supply equation.[22] Since price is endogenous, we use two-stage least squares and instrument using the monthly quantity demanded given that the demand for wholesale electricity is completely inelastic. The dependent variable, as discussed in Section 4.2, is in levels in all 4 specifications considered. 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 6,043 MWh and \$50 per MWh is 0.74.

Exogenous State Variables. Figure 7 shows the paths for various of the exogenous state variables in the model for 2013–2062. 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, estimated in the residual demand curve, and have that increase at a rate of 1% per year from that point onwards. Within each year, 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, within each month, there will be 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

[22] We refer the reader to Section A.3 for some additional descriptive statistics.

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]

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 CAGR (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]

Policy Equations. 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-squared 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. In the case of the band equations, we set $\lambda_1^B = 0$ and $\lambda_2^B = 0.10$ for both coal and gas in the current set of results. The implication is that there is no adjustment to capacity in the next period if the target level is within that range.

Structural Estimates. The estimate reported in Table 7 is \$/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

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

MW for gas-fired capacity is comparable to the estimates in Spees et al. (2011), which are up to $1 million per MW. Furthermore, as we have already discussed, the reported standard error of approximately $32,000 per MWh does not take into account the 1st-stage estimation error.

Endogenous Variables. We also provide the paths for a variety of endogenous variables, such as market-wide outcomes, and firm-level generation, profits, capacity, and heat rates, from our forward simulations for 2013–2062.[25] The BAT capacity in Figure 9, 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 price (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 8.

Model Predictions. Finally, in Figure 10 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.[26] As we can see, our model tracks reasonably well the NYMEX futures prices.[27]

[25] All dollars are nominal.

[26] 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, 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.

[27] In Figure A3, we compare the behavior of heat rates, fuel prices, generation and capacity before and

6 Counterfactual Simulations

We use the estimated model to compare welfare under counterfactual CO_2 emissions regulations implemented at the regional level (single market) and at the individual state level (separate markets). We begin our welfare analysis by looking at the "static" case, where we compute welfare outcomes holding BAT capacity fixed. In this case, investment is exogenous and BAT capacity is the same with single and separate CO_2 markets. We then shift our focus to the "dynamic" case, where investment is a result of optimal behavior of firms and so BAT capacity is endogenous. Welfare with single and separate CO_2 markets is now influenced by differences in investment incentives in the two regulatory regimes.

To evaluate and compare market outcomes, we assume that PJM states are subject to the mass-based targets of the Clean Power Plan (CPP) given 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 shown in the table. With a single CO_2 market, there is an aggregate (PJM-wide) target for emissions, which is the sum of the targets across the PJM states shown in Figure 11. Although we do not explicitly model a market for emissions permits, one can think of the shadow price of the CO_2 emissions constraint as the price that clears the market for permits. In the case of a single CO_2 market, there is one permit price. In the case of separate CO_2 markets, the permit prices are state-specific and correspond to each state's constraint.

The CO_2 price increases the cost of generating electricity for power plants, which in turn affects the industry supply curve in the wholesale electricity market. This additional cost is different for sources with different heat rate-adjusted emission rates (lbs./MMBtu). Hence, we compute the marginal cost for source i in state s at time t as follows:

$$c^C_{ist} = c_{ist} + P^C_{st} \times r^C_{ist} \times \zeta, \tag{25}$$

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 11 PJM states listed in Table 2.

The CO_2 price affects plants' costs and hence the supply curve. Equilibrium demand 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.

supply in the wholesale electricity market determine which plants are called to serve demand which would determine total emissions. The amount of emissions then determines how much the emissions target binds and hence the equilibrium CO_2 price. Therefore, obtaining the equilibrium wholesale electricity and CO_2 prices requires the simultaneous clearing of the wholesale electricity and emissions markets. We discuss the algorithm to find the equilibrium in Section A.6.

6.1 Static Analysis: Exogenous Investment

Holding capacity fixed, welfare with a single CO_2 market is expected to be higher than welfare with separate CO_2 markets. A single CO_2 market equates marginal CO_2 abatement costs across markets, leading to lower overall compliance costs. Nevertheless, an integrated *product* (electricity) market can mitigate inefficiencies associated with separate CO_2 markets as long as output from high CO_2 price markets can be reallocated to low CO_2 price markets, all else equal.

We solve for the equilibrium of the electricity and CO_2 market(s), allowing the BAT capacity to vary exogenously between 0 and 60,000 MW in 2030, noting that the qualitative nature of our findings is similar for all years between 2022 and 2030. Figure 12 (panel (a)) shows the cost of producing electricity with single and separate CO_2 markets as a function of these exogenous levels BAT capacity. As the figure illustrates, there is practically no difference in the cost of producing electricity between single and separate CO_2 markets for high and low levels of BAT capacity.

We see a wedge in costs only for intermediate levels of BAT capacity. In the case of high BAT capacity levels—in excess of 50,000 MW—the equality in cost across single and separate CO_2 markets is explained by the fact that the state-specific CO_2 targets no longer bind due to abundant capacity exempt from the targets. The slackness of the constraints associated with the CO_2 targets implies zero CO_2 prices even in the case of separate markets. With low BAT capacity levels—generally, below 10,000 MW—there is little electricity generation associated with capacity exempt from the targets. As a result, CO_2 prices that hit the ceiling of \$100 even with a single CO_2 market are needed to meet the targets. The largest difference in cost is \$2.5 billion at BAT capacity of 32,000 MW. This difference is about 50% of CPP compliance cost, which is computed by taking the difference in electricity generation and investment cost with and without the CPP, assuming a single CO_2 market.

We also compute total welfare excluding cost of investment with single and separate CO_2 markets. Depending on the exogenous level of BAT capacity, we see values between \$122 and \$141 billion with the largest divergence of \$0.5 billion occurring at a BAT capacity of 43,000 MW (Figure 12, panel (b)).

6.2 Dynamic Analysis: Optimal Investment

In this section, we use the dynamic model that we have set up and estimated previously to study the firms' optimal response to environmental policies with alternative scenarios. In our first benchmark scenario, we compute optimal investment assuming a social planner maximizing total surplus. In our second benchmark scenario, we compute investment assuming nonstrategic firm behavior. We then explore the outcomes of different combinations of assumptions on strategic investment behavior and integration of CO_2 markets.

We make a series of assumptions throughout the analysis, all of them consistent with the specific details of the Clean Power Plan (CPP). First, only emissions from existing capacity built by 2012 are subject to CO_2 prices; emissions from capacity built after 2012 are exempt from the CO_2 price. However, post-2012 capacity must have the best available technology (BAT) in the sense of having the lowest heat and emissions rate during the investment year. Second, we assume that heat rate improvements are exogenous.[28] Third, generation from renewable sources increases exogenously according to the annual growth rates in the CPP.[29] Finally, we assume an upper bound of \$100 for the CO_2 price and set the post-2030 CPP targets at their 2030 levels.[30]

6.2.1 Social Planner and Nonstrategic Investment

The social planner chooses investment to maximize the present 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, where we assume a social cost of carbon equal to \$37 per metric ton.

[28] See discussion on exogenous state variables in Section 5.3, as well as the additional details in Section A.7.

[29] 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.

[30] 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.

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. We refer to this latter scenario as the scenario with *nonstrategic investment*. Bushnell et al. (2017b) refer to this kind of scenario as a scenario with competitive investment. We simulate the nonstrategic investment scenario with single and separate CO_2 markets.

Steady state (2030) BAT capacity assuming a social planner is 34,250 MW (Table 9). In the case of nonstrategic investment, BAT capacity is 48,150 MW with a single CO_2 market while BAT capacity is 51,300 MW with separate CO_2 markets. Since 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 a 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. Present discounted welfare for the social planner is \$1,142 billion. In the case of the nonstrategic investment, welfare is \$1,134 billion with a single CO_2 market and \$1,133 billion with separate CO_2 markets.

The difference in welfare between the social planner and nonstrategic investment scenarios are driven by how damages from CO_2 emissions enter the objective function for investment. Unlike the social planner case, nonstrategic investment imperfectly internalizes damages from CO_2 emissions through the CO_2 market. Even with a single CO_2 market, since BAT capacity is not subject to a CO_2 price, there will be over-investment similar in nature to what the literature refers to as emissions leakage (Fowlie, 2009). With separate CO_2 markets, the incentive to invest is even greater, exacerbating over-investment and the emissions leakage problem. Note however that the welfare difference between single and separate CO_2 markets is small and is not driven by the lack of coordination of CO_2 markets across states per se, but by the regulatory treatment of investment.[31] Moreover, the present discounted value of electricity production costs is actually lower (\$9.6 billion) with separate CO_2 markets than with a single CO_2 market (\$12.3 billion).

6.2.2 Strategic Investment

Single Firm. This is an extreme case where the strategic firms fully coordinate investment to maximize the sum of their profits. Steady state BAT capacity in the case of a single CO_2 market is suppressed to 4,000 MW raising average electricity prices to \$89 per MWh.

[31] See Section A.8 for a different regulatory treatment of new plants.

Welfare goes down to \$1,130 billion. In contrast, steady state BAT capacity with separate CO_2 markets is much higher at 11,300 MW raising electricity prices to \$86 per MWh. Interestingly, 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). This is the case because firm invest in generating units that are more efficient (produce fewer CO_2 emissions per unit of electricity produced) than existing units.

Welfare with separate CO_2 markets is \$1,139 billion, which is larger than its counterpart with a single CO_2 market. It may seem surprising that settings with an inherent inefficiency–absence of a single market for correcting the externality–yield higher total welfare. However, this inefficiency is 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 have a strong incentive to withhold investment. The additional incentive to invest that separate CO_2 markets create in this case is welfare-enhancing, leading to *higher* welfare compared to the case of a single CO_2 market.

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.[32] 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. Under the assumption of competitive wholesale markets, 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.

[32]Since the state space grows exponentially with the number of firms, we only consider a two-firm investment game when we explore the strategic use of investment to alleviate some of the computational burden that the solution of the model entails. In addition, although our empirical model allows for privately-observed investment cost shocks, we do not identify the distribution of these shocks. Hence, we solve a game of complete information. In this case, since the existence of a pure strategy equilibrium is not guaranteed (Doraszelski and Satterthwaite (2010)), we assume a sequential game of investment for each period. This assumption not only addresses the existence but also the uniqueness of the equilibria. See Bresnahan and Reiss (1990) Berry (1992) for early examples in static entry game setting, and, more recently, Abbring and Campbell (2010) in an infinite-horizon setting.

Introducing competition mitigates the incentives for firms to strategically withhold investment in order to raise prices. It is still the case, however, that a two-firm game implies under-investment. Total BAT capacity is 10,400 MW and 17,850 MW for single and separate CO_2 markets, respectively, which are both lower than the socially-optimal level, but both higher than in the case with fully coordinated investment. In this two-firm setting, competitors are able to raise prices above efficient levels but not as much as a monopolist would do: electricity prices are now \$72 per MWh (single CO_2 market) and \$67 per MWh (separate CO_2 markets).

It is still the case that separate CO_2 markets dominate a single CO_2 market in terms of total welfare. The difference is \$3.8 billion and is explained by the fact that investment rates are closer to efficient levels in the separate CO_2 markets scenario. Moreover, competition has the effect that most of the added new capacity is built earlier (even when compared to the case of a social planner). This is because the leader in the investment game will try to preempt its rival. As a result, unsurprisingly, most of the investment is undertaken by the leader.

7 Conclusion

In this paper, we show that separate markets for an environmental externality, which may emerge due to lack of policy 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.

We set up and estimate a dynamic structural model of production and investment for the largest wholesale electricity market in the world, the Pennsylvania-New Jersey-Maryland (PJM) Interconnection. There are targets for carbon dioxide (CO_2) emissions associated with electricity generation achieved via a market for emission permits with two different implementation regimes. With regional implementation, there is a single CO_2 market. With state-by-state implementation, there are separate CO_2 markets, one for each of the states participating in PJM.

Our model preserves the rich plant-level cost heterogeneity in the data while being tractable enough to evaluate market outcomes across the two implementation 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 interesting question which can be answered using our framework is whether states have unilateral incentives to adopt emission restrictions in the absence of any federal mandate. The potential benefit of doing so would be to provide incentives for investment in more efficient capacity, 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.

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8 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 3.1.

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	CO_2 Emissions tons million	Electricity Costs $ billion	Consumer Surplus $ billion	Firm Profit $ billion	CO_2 Damages $ billion	CO_2 Revenues $ billion	Total Welfare $ billion
SOCPLAN	34,250	34	374.2	44.8	1,107.8	154.1	119.7	0.0	1,142.2
NST-SIN	48,150	28	414.3	12.3	1,146.9	118.9	131.4	0.0	1,134.4
NST-SEP	51,300	27	419.3	9.6	1,148.8	116.5	132.7	0.2	1,132.8
1F-SIN	4,000	89	270.1	211.7	780.1	348.9	91.9	92.9	1,129.9
1F-SEP	11,300	86	258.1	180.8	800.0	353.9	88.7	73.4	1,138.5
2F-SIN	10,400	72	298.5	147.4	864.4	309.1	99.9	63.8	1,137.5
2F-SEP	17,850	67	311.7	104.3	893.6	305.3	104.0	46.4	1,141.3

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. Total welfare equals consumer surplus (CS) plus firm profit minus environmental damages calculated using social cost of carbon ($37/metric ton) plus revenues from the CO_2 market(s). 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.

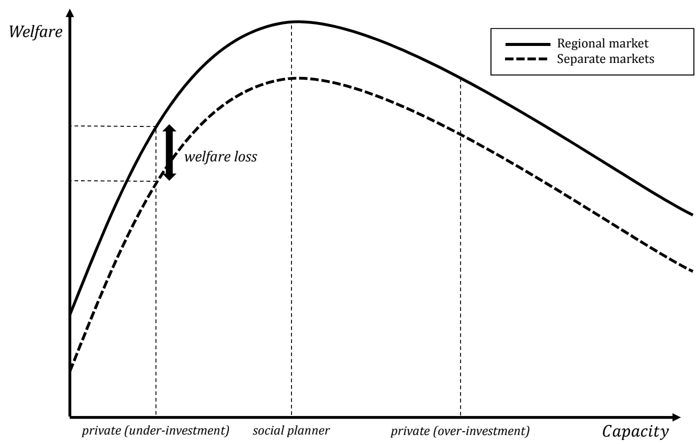
Table 10: Description of alternative investment scenarios

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

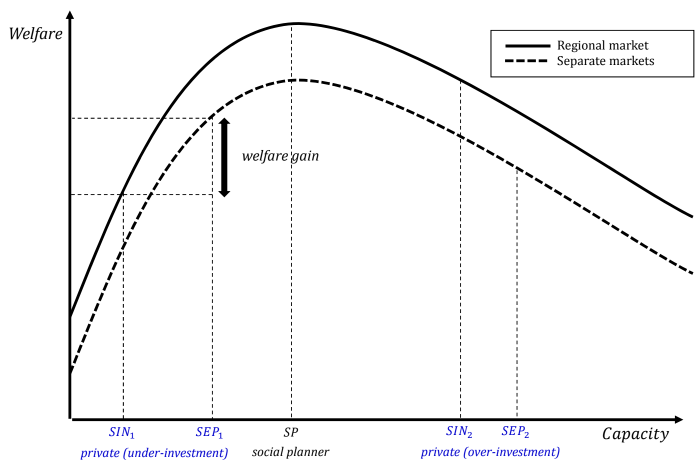
Note: the table provides a brief description of the alternative investment scenarios discussed in detail in Section 6.

9 Figures

Figure 1: Economic intuition



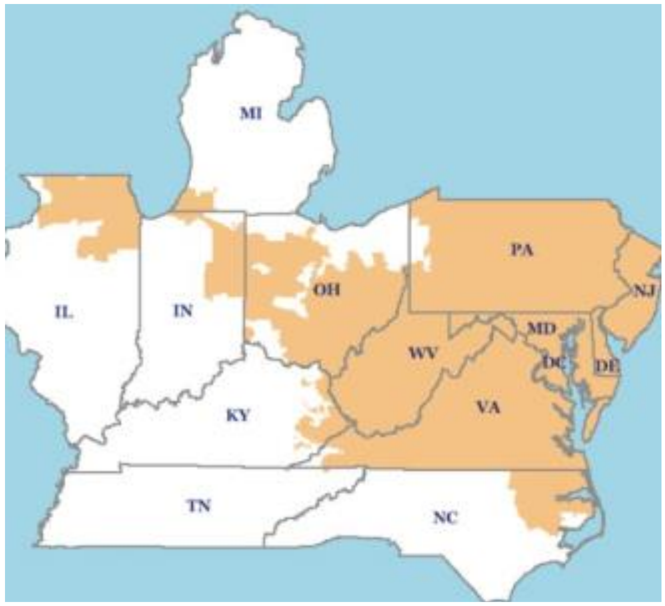
(a) static model



(b) dynamic model

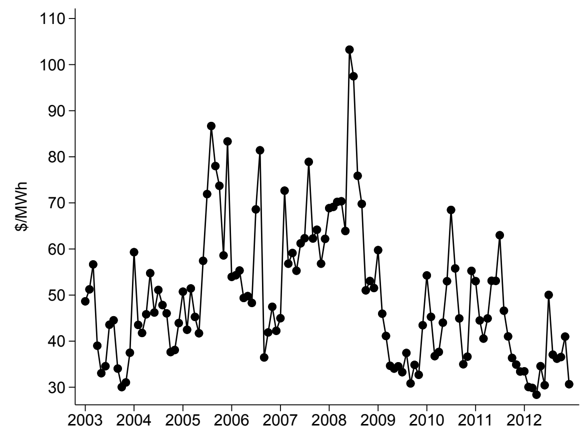
Note: This figure plots the total welfare obtained under a single market for the externality and separate markets, for different capacity levels. In particular, for the social planner's choice of capacity, or for the private optimal (in the case of both under- or over-investment. Panel (a) represents a static approach, where capacity does not adjust when we move from a single market to separate markets. Panel (b) allows capacity choices to adjust to the type of the market for the externality.

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

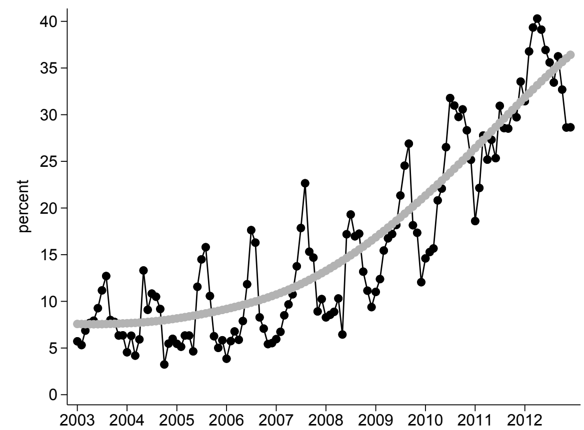


Source: http://ieefa.org/pjms-reform/

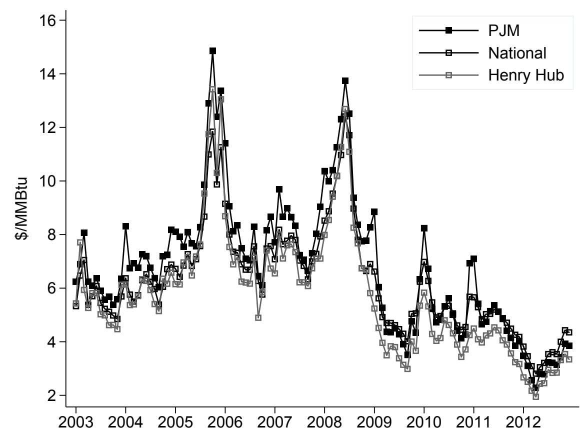
Figure 3: Electricity and fuel prices (2003–2012)



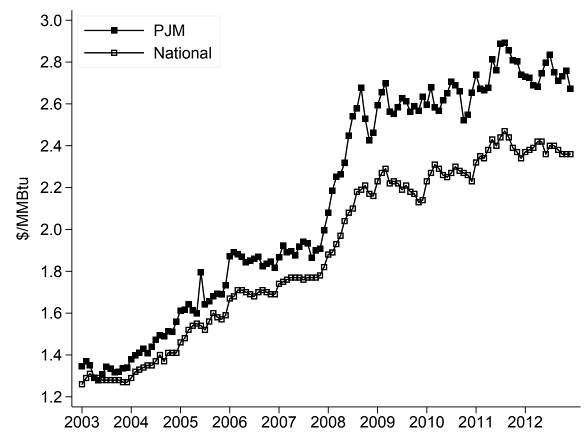
(a) Electricity prices



(b) Gas share of net generation



(c) Gas prices



(d) Coal prices

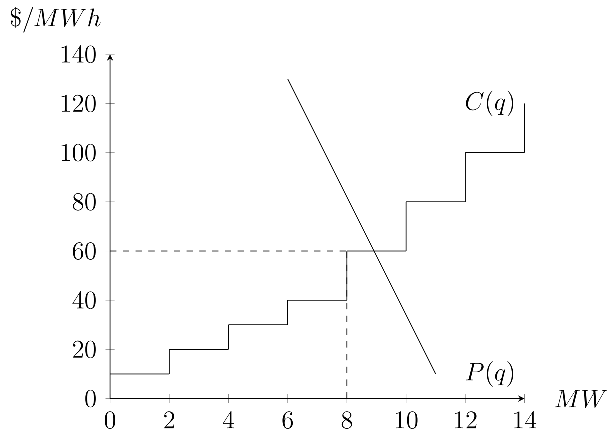
Note: The electricity prices are monthly load-weighted system-wide real-time prices from PJM. The coal and gas prices are from EIA. In panel (b), we plot the gas share of coal plus gas net generation for power plants in PJM using data from EIA.

Figure 4: Overview of the model timing

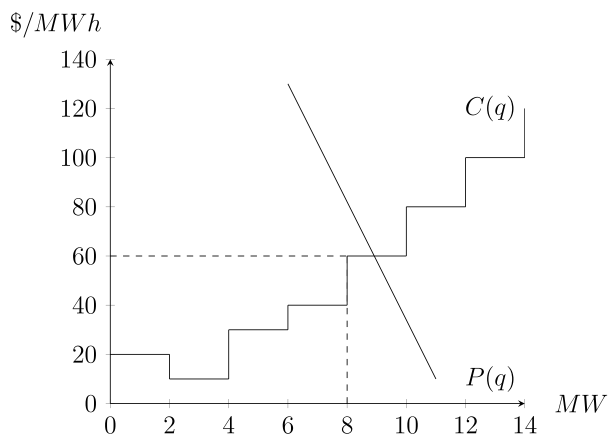
$$\begin{array}{ccccc}
2012 & \longrightarrow & 2013 & \longrightarrow & 2014 \\
 & \underbrace{\begin{array}{c}\text{Demand parameters} \\ \text{Cost functions}\end{array}}_{\text{Electricity Market}} & \begin{array}{c}\Big\downarrow \\ \textbf{Investment}\end{array} & \underbrace{\begin{array}{c}\text{Demand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

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

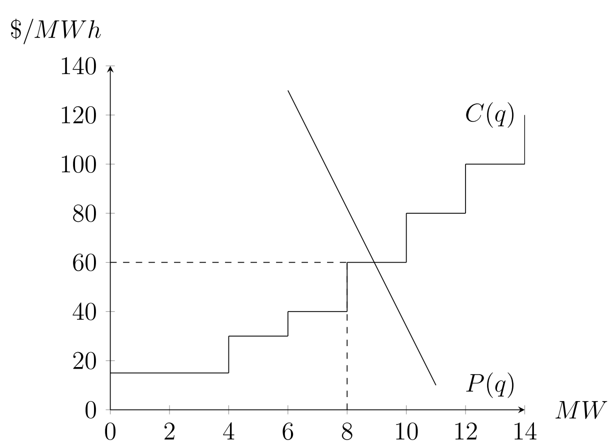
Figure 5: Merit order invariance with inframarginal units



(a) Demand and supply

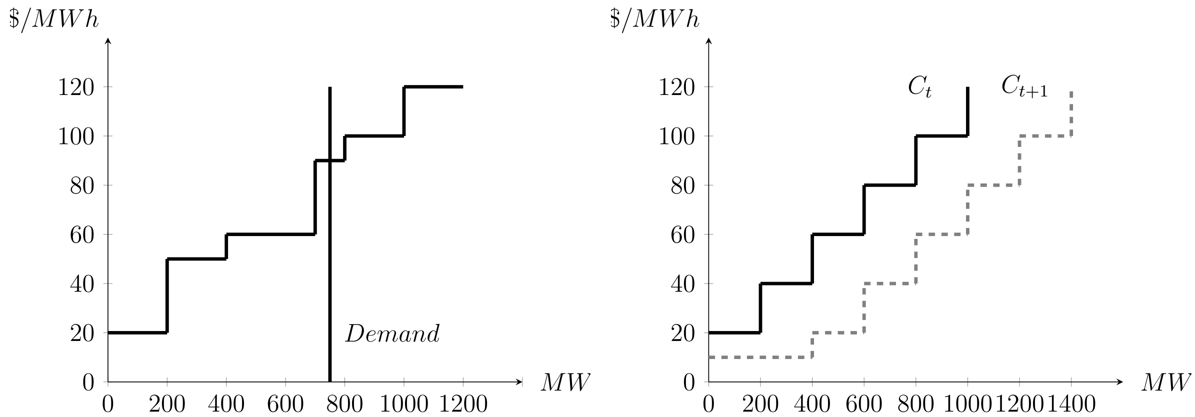


(b) Invariance to rearrangement



(c) Invariance to averaging

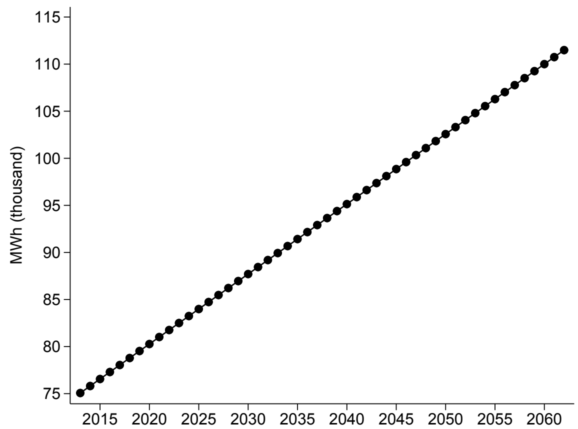
Figure 6: Merit order and best available technology



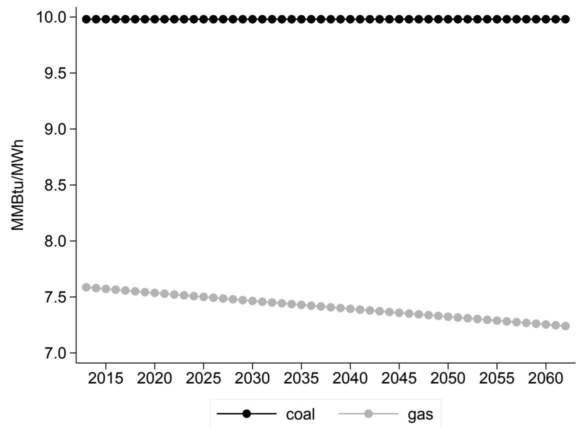
(a) merit order (b) best available technology

Note: In panel (a), the step function emerges by ordering available sources to serve demand in terms of their marginal costs. The sources with the lowest (highest) costs are ordered first (last). In panel (b), The step function C_t (black solid line) indicates the marginal cost curve prior to investment at time t. 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 $t + 1$.

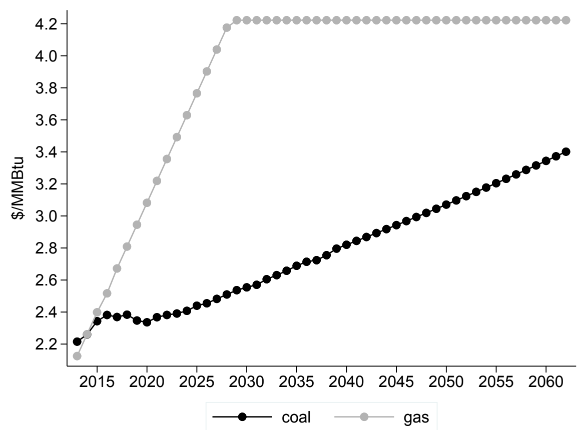
Figure 7: Paths of exogenous variables, 2013–2062



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

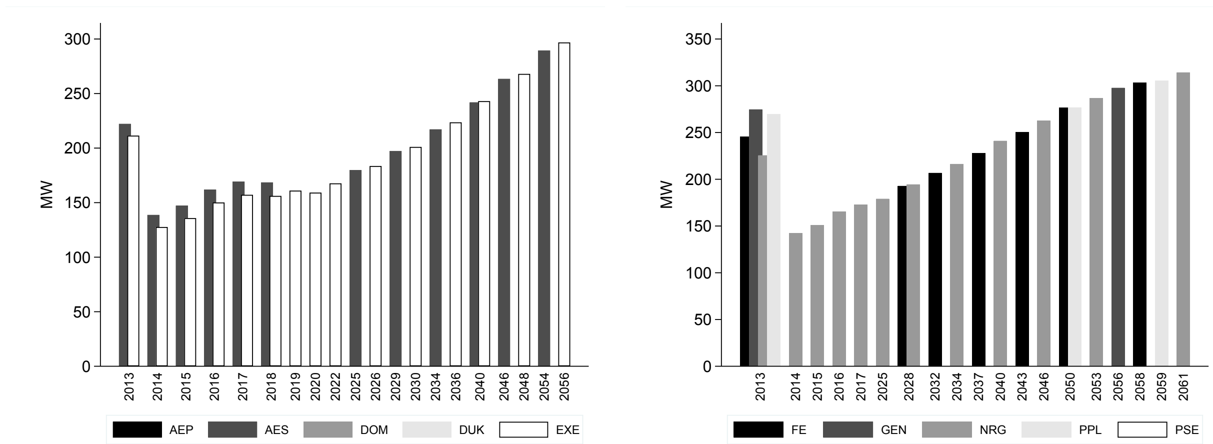


(b) heat rates for new investment



(c) fuel prices

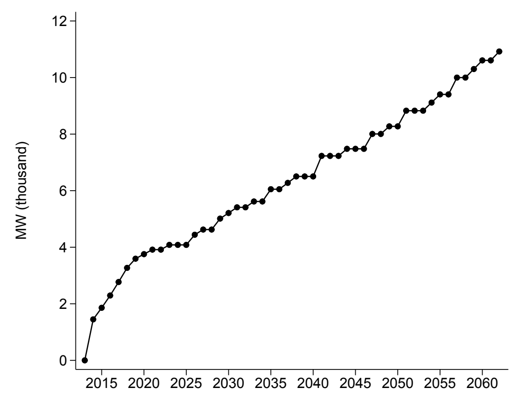
Figure 8: BAT Investment in gas-fired capacity, 2013–2062



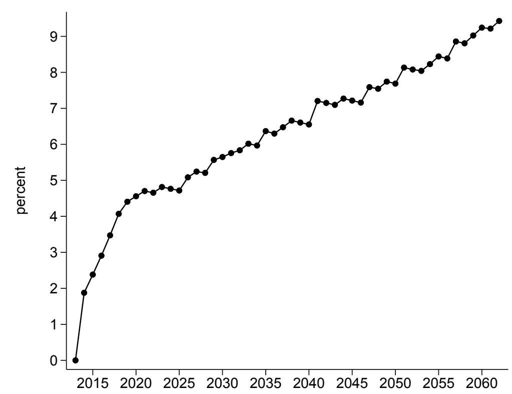
(a) 1st group (b) 2nd group

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.

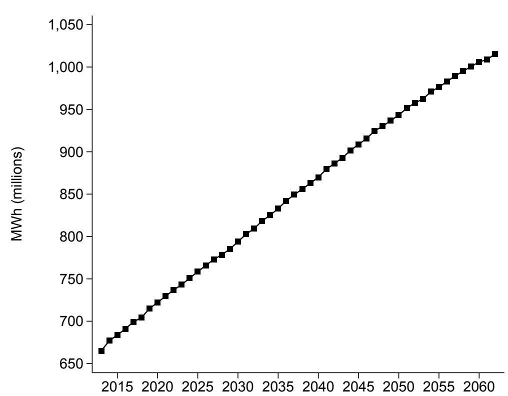
Figure 9: Paths of endogenous variables, 2013–2062



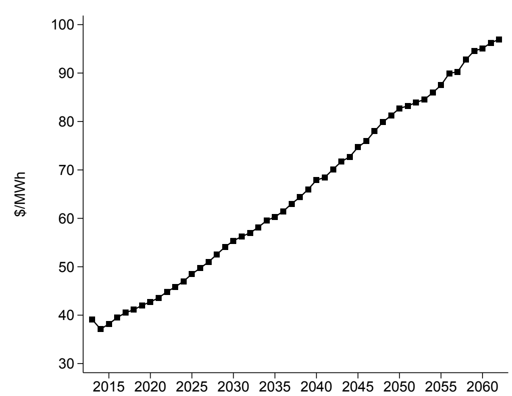
(a) BAT capacity



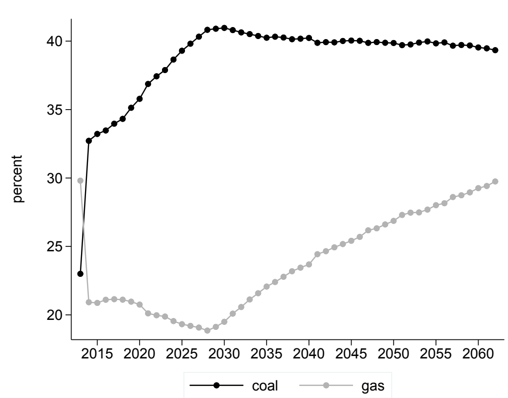
(b) BAT capacity: generation %



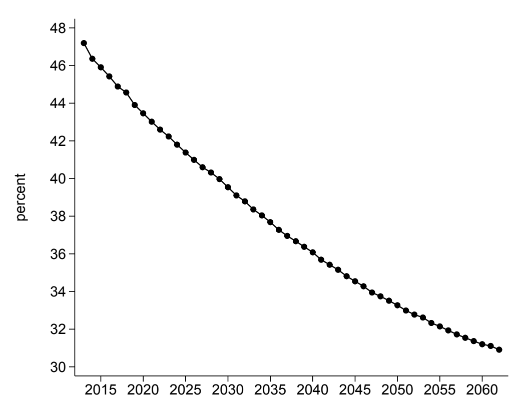
(c) electricity generation



(d) electricity price



(e) electricity generation % from coal and gas



(f) electricity generation % from other fuels

Note: BAT refers to best available technology.

Figure 10: Electricity prices implied by the model compared to NYMEX futures

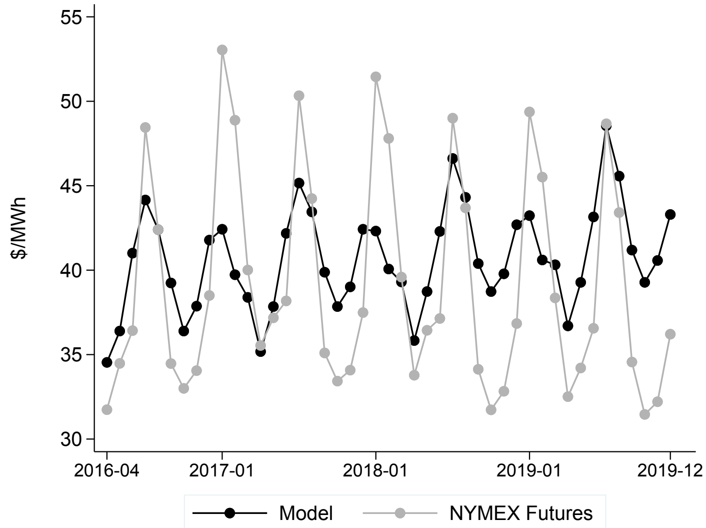
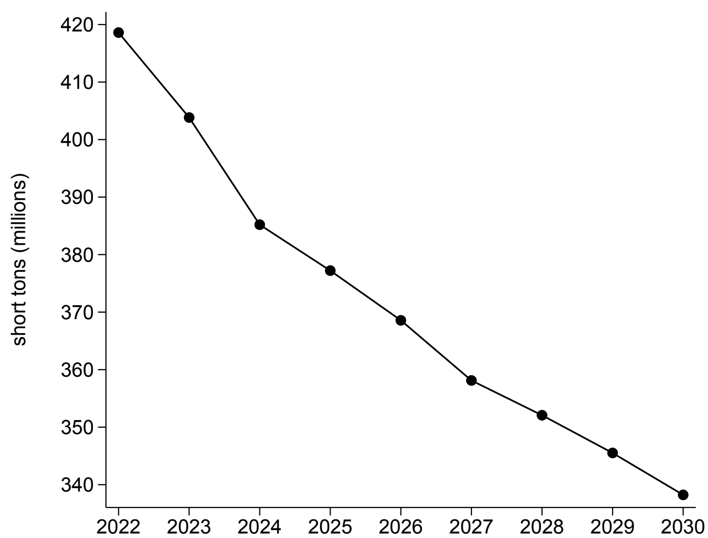
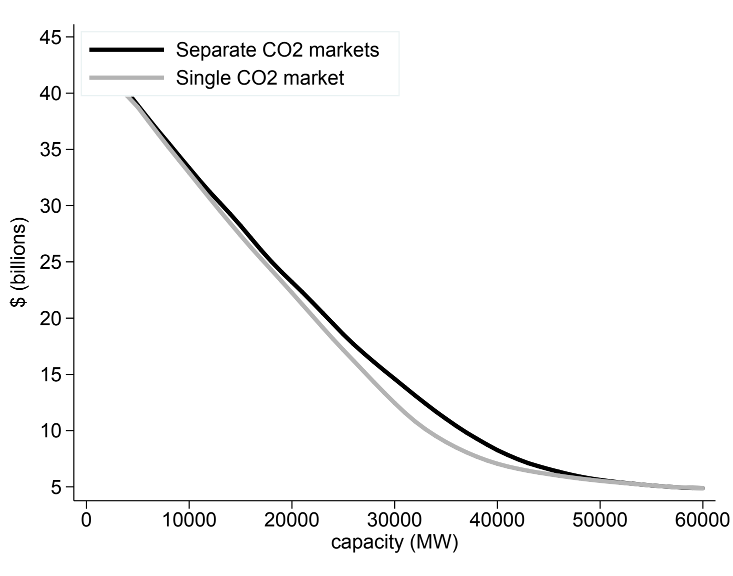


Figure 11: Regional CPP mass-based targets

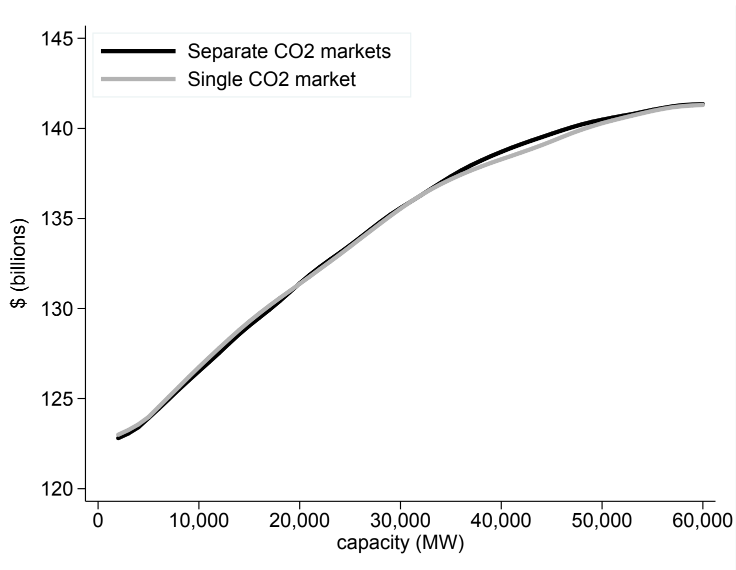


Note: The mass-based target in this figure is based on the supporting data file for CPP compliance from PJM (2016) and are based on electric generating units in the PJM footprint for each state noting that PJM covers only parts of IL, IN, KY, and NC. We plot the sum of state mass-based targets from panel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

Figure 12: Electricity generation cost and total welfare for the exogenous investment scenario



(a) cost of generating electricity



(b) total welfare

Note: The figure shows electricity generation cost in 2030 as a function of BAT capacity with single and separate CO_2 markets. BAT refers to best available technology.

A Online Appendix

NOT FOR PUBLICATION

A.1 Stylized Model

We illustrate the inefficiencies that arise with uncoordinated emissions regulations and how a single product market can mitigate these inefficiencies. We also examine the role of investment as the main mechanism for coordinating uncoordinated regulations.

We make a series of assumptions for the purpose of illustration. First, we assume that there are only two states, say, Pennsylvania (PA) and Delaware (DE). Second, there is a single electricity-generating firm. The firm produces quantities q_{PA} and q_{DE} of electricity in plants located in states PA and DE, respectively. The firm can reduce its CO_2 emissions in state PA (DE) by an amount a_{PA} (a_{DE}). The firm's total cost function is given by $C(q_{PA}, q_{DE}, a_{PA}, a_{DE})$. Furthermore, there is a single wholesale electricity market covering both states and the firm acts as a price taker. Let p be the wholesale electricity price and consider a mass-based target for CO_2 emissions while assuming that one unit of electricity generation implies one unit of emissions. Denote the mass-based targets as X_{PA} and X_{DE}.

Regional compliance requires:

$$(q_{PA} - a_{PA}) + (q_{DE} - a_{DE}) \leq X_{PA} + X_{DE}. \tag{A1}$$

State compliance requires:

$$q_{PA} - a_{PA} \leq X_{PA} \tag{A2}$$

$$q_{DE} - a_{DE} \leq X_{DE}. \tag{A3}$$

Without loss of generality, suppose that there is a *capacity* constraint in state DE. For simplicity, we express the capacity constraint as a constraint on output: let Q be the maximum total output that plants in state DE can produce. The firm can relax the capacity constraint by investing in new capacity that increases Q by i, i.e. next period's maximum total output is now $Q' = Q + i$. Assume total investment has cost $\Gamma(i)$.

We assume that the cost function depends only on the *sum* of output across the two states, i.e. $C(q_{PA}, q_{DE}, a_{PA}, a_{DE}) = C(q_{PA} + q_{DE}, a_{PA}, a_{DE})$. Hence, cost convexities arise only through the output constraint. Given the cost assumption, the firm's profit in each period t is given by:[33]

$$\pi(\mathbf{q_t}, \mathbf{a_t}) = p \times (q_{PAt} + q_{DEt}) - C(q_{PAt} + q_{DEt}, a_{PAt}, a_{DEt}). \tag{A4}$$

[33] For simplicity, we assume that $p_t = p$ for all t.

The firm chooses electricity generation, emissions reduction, and investment in order to maximize its present discounted sum of profits:

$$\sum_{t=0}^{\infty} \beta^t \left[\pi(\mathbf{q_t}, \mathbf{a_t}) - \Gamma(i_t)\right]. \tag{A5}$$

The firm's profit maximization is subject to the capacity constraint, and either the regional or state-by-state CO_2 compliance constraint. The corresponding Bellman equation (constraints suppressed) is given by:

$$V(Q) = \max_{\mathbf{q},\mathbf{a},i} \pi(\mathbf{q}, \mathbf{a}) - \Gamma(i) + \beta V(Q'). \tag{A6}$$

The following lemma is useful in characterizing the solution to the firm's maximization problem:

Lemma 1. *Let $\eta \geq 0$ be the Lagrange multiplier for the output constraint. For both regional and state compliance:*

$$V(Q) = \widetilde{V}(Q; \eta) + \textit{constant}, \tag{A7}$$

where $\widetilde{V}'(Q;\eta) = 0$ when $\eta = 0$, and $\widetilde{V}'(Q;\widetilde{\eta}) > \widetilde{V}'(Q;\eta)$ for $\widetilde{\eta} > \eta$.[34]

Proof. Let $\eta \geq 0$ be the Lagrange multiplier for the output constraint, and $\lambda \geq 0$ for the CO_2 emissions constraint ($\lambda_{PA} \geq 0$ and $\lambda_{DE} \geq 0$ for state compliance). We start by conjecturing the solution, $V(Q) = \widetilde{V}(Q;\eta) + \text{constant}$, with $\widetilde{V}'(Q;0) = 0$ and $\widetilde{V}'(Q;\eta)$ increasing in η, and then solve the problem to confirm the consistency of the conjecture.

Consider regional compliance. Suppose Q is large enough such that capacity does not bind at the optimum, i.e. $\eta = 0$. Thus $\eta = 0$ and so $V'(Q') = 0$ under our conjecture. Since the marginal benefit of investment is equal to $\beta V'(Q')$, then $i^* = 0$ and $Q' = Q$. Therefore, we have:

$$V(Q) = \frac{1}{1-\beta}\left[\pi(q_A^*, q_B^*, a_A^*, a_B^*) + \lambda^* \left\{ \begin{array}{c} X_A + X_B \\ -(q_A^* - a_A^*) - (q_B^* - a_B^*) \end{array} \right\}\right], \tag{A8}$$

where $(q_A^*, q_B^*, a_A^*, a_B^*)$ solve the first order conditions with respect to output and abatement. Since none of the first order conditions are functions of Q when $\eta = 0$, optimal output and abatement levels are also not functions of Q. Hence $V(Q)$ is just a constant and therefore $V'(Q) = 0$. The same argument holds for state compliance.

[34] Formally, η is a function of (Q, X_{PA}, X_{DE}) so the conditions correspond to (1) a triplet (Q, X_{PA}, X_{DE}) such that $\eta(Q, X_{PA}, X_{DE}) = 0$, and (2) a pair of triplets (Q, X_{PA}, X_{DE}) and $(Q, \widetilde{X}_{PA}, \widetilde{X}_{DE})$ such that $\eta(Q, \widetilde{X}_{PA}, \widetilde{X}_{DE}) > \eta(Q, X_{PA}, X_{DE})$.

Now suppose Q is such that $\eta > 0$. This implies $q^*_{DE} = Q$, and so $V(Q)$ will be some function of Q. The envelope theorem implies $V'(Q) = \eta + \widetilde{V}'(Q'; \eta)$ which is indeed increasing in η under our conjecture. Again, the same argument holds for state compliance. $\square$

We first solve the regional compliance case. The first order conditions for output and abatement imply the following:

$$p = \frac{\partial C}{\partial q_{PA}} + \lambda = \frac{\partial C}{\partial q_{DE}} + \lambda + \eta. \tag{A9}$$

Since $\frac{\partial C}{\partial q_{PA}} = \frac{\partial C}{\partial q_{DE}}$ for all q_{PA} and q_{DE} under our assumed cost function, we have $\eta = 0$. Intuitively, the output constraint never binds since the firm can freely reallocate production between the two states without impacting total cost. The lemma above implies $V'(Q) = 0$ when $\eta = 0$. Hence, the marginal benefit of investment is zero and thus investment is zero ($i^* = 0$). Finally, output and abatement are the solutions to the following equations:

$$\frac{\partial C}{\partial a_{PA}} = \frac{\partial C}{\partial a_{DE}} \tag{A10}$$

$$\frac{\partial C}{\partial q_{PA}} = \frac{\partial C}{\partial q_{DE}}. \tag{A11}$$

We refer to an allocation $(q^*_{PA}, q^*_{DE}, a^*_{PA}, a^*_{DE})$ as *efficient* if it solves Equation A10 and Equation A11. The optimal allocation under regional compliance is efficient. For our first result, we show that as long as Q is sufficiently large, then the optimal solution under *state compliance* is efficient as well. The key idea is that the firm will reallocate output across states to balance CO_2 price differences. When there is enough capacity to facilitate the desired reallocation, then CO_2 prices will converge to a single value.

Proposition 1. *As long as the capacity constraint is non-binding, the solution under state compliance is efficient.*

Proof. The first order conditions for output and abatement imply:

$$p = \frac{\partial C}{\partial q_{PA}} + \lambda_{PA} \tag{A12}$$

$$p = \frac{\partial C}{\partial q_{DE}} + \lambda_{DE} + \eta. \tag{A13}$$

Consider a solution where the capacity constraint is non-binding. Thus, the first order conditions simplify to

$$\frac{\partial C}{\partial q_{DE}} - \frac{\partial C}{\partial q_{PA}} = \lambda_{PA} - \lambda_{DE}.$$

Since $\frac{\partial C}{\partial q_{PA}} = \frac{\partial C}{\partial q_{DE}}$ for all q_{PA} and q_{DE} under the assumed cost function, $\lambda_{PA} = \lambda_{DE}$ and marginal abatement costs across the two states are equal. □

For low levels of capacity in DE, the capacity constraint may bind and it would be optimal to invest under state compliance. The extent that the capacity constraint binds turns out to be related to the difference in CO_2 prices, hence, to the difference in marginal abatement costs, across states. Thus, the friction introduced by uncoordinated CO_2 regulation will drive incentives to invest as the following proposition summarizes.

Proposition 2. *The marginal benefit of investment is greater when CO_2 prices are more dispersed across states (e.g. $\lambda_{PA} \gg \lambda_{DE}$), i.e. there is greater mismatch in marginal abatement costs. Therefore, the incentives to invest are higher. As a result, future mismatch in marginal abatement costs is reduced. If investment costs a low enough, then the stead state solution is efficient.*

Proof. The output and abatement FOCs, along with the assumption on the cost function, imply:

$$\eta = \lambda_{PA} - \lambda_{DE} = \frac{\partial C}{\partial a_{PA}} - \frac{\partial C}{\partial a_{DE}} \geq 0.$$

We show that the value function $V(Q)$ is such that $V'(Q)$ is increasing in η.

The marginal benefit of investment is $\beta V'(Q)$ with corresponding FOC:

$$\Gamma(i) = \beta V'(Q).$$

Hence, a larger η implies a greater marginal benefit from investment and greater incentives to invest.

With $i > 0$, next period's capacity constraint in DE is relaxed, which allows output to be transferred from PA to DE, relaxing CO_2 emissions constraint in PA. Thus, $\lambda_{PA} - \lambda_{DE}$ decreases. If investment costs are low enough, $\lambda_{PA} - \lambda_{DE} \downarrow 0$ in the steady state. □

To summarize, we have shown through a stylized model that in the presence of an integrated product market and in the absence of frictions, single and separate CO_2 markets both yield efficient solutions. The main drivers behind this result are perfect reallocation of output and CO_2 price adjustments. We also show that with separate markets, there is an added benefit to investment. When CO_2 price differences are significantly large, the firm would like to reallocate output. However, capacity constraints may prevent it from doing so. Investment facilitates reallocation of output when capacity constraints are binding. Importantly, the marginal benefit of investment is positively related to the dispersion in CO_2 prices across states.

In terms of social welfare, actual investment may be too small for, at least, two reasons. First, the constraints imposed on CO_2 emissions may be too lenient due to political reasons, and, hence, not enough to encourage investment in cleaner capacity. Second, firms may exercise market power in the wholesale energy market by withholding capacity and delaying retirements and investment. Hence, new capacity with separate CO_2 markets may actually be closer to the socially optimal level compared to the case with a single CO_2 market.

A.2 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.[35]

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.[36] 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.[37] The annual data on plant

[35]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.

[36]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.

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

operating expenses are from SNL.[38]

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.[39] 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 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.[40]

The SO_2 and seasonal NO_x permit prices are from Evolution Markets, a permit brokerage firm we identified from the EPA website.[41] The Weather used in the estimation of the fringe supply equations are from the National Oceanic and Atmospheric Administration (NOAA).[42]

A.3 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.

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

[39] 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.

[40] 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.

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

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

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.[43] 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 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.4 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

[43] 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.

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.5 Investment Cost Heterogeneity

We now present in more detail the estimation routine for the investment cost parameters and, in particular, we explain how the procedure allows for heterogeneity that follows a distribution for which we estimate the first moment and remain agnostic about the second moment. 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:

$$\Gamma_{jt} = \gamma_{jt} \times i_{jt}^{ng}, \tag{A14}$$

where $\gamma_{jt} = \overline{\gamma} + \nu_{jt}$ with ν_{jt} being a privately known shock that is IID across firms and time and follows the common distribution $G_{\nu}(0, \sigma_{\nu}^2)$. 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:

$$\begin{aligned} E_{\nu_{jt}}\left[\pi_{jt}\right] = \overline{\pi}_{jt} - E_{\nu_{jt}}\left(\gamma_{jt} i_{jt}^{ng}\right) &= \overline{\pi}_{jt} - E_{\nu_{jt}}\left(\gamma_{jt}\right) E_{\nu_{jt}}\left(i_{jt}^{ng}\right) - Cov\left(\gamma_{jt}, i_{jt}^{ng}\right) \\ &= \overline{\pi}_{jt} - \overline{\gamma} E_{\nu_{jt}}\left(i_{jt}^{ng}\right) - Cov\left(\gamma_{jt}, i_{jt}^{ng}\right) \end{aligned} \tag{A15}$$

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:

$$\begin{aligned} E_{\nu_{jt}}\left[\widetilde{\pi}_{jt}\right] &= \overline{\pi}_{jt} - \overline{\gamma} E_{\nu_{jt}}\left(\widetilde{i}_{jt}^{ng}\right) - Cov\left(\gamma_{jt}, \widetilde{i}_{jt}^{ng}\right) \\ &= \overline{\pi}_{jt} - \overline{\gamma}\left(E_{\nu_{jt}}\left(i_{jt}^{ng}\right) + \chi\right) - Cov\left(\gamma_{jt}, i_{jt}^{ng}\right). \end{aligned} \tag{A16}$$

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 (A15) and the value function based on (A16) 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.6 Emissions Market Clearing Algorithm

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:

$$P_t^C = \min\{P : \sum_{s \in S} \sum_{i \in s} (q_{ist}(P) \times HR_{ist} \times r_{ist}) \leq \sum_{s} \overline{E}_{st}\}. \tag{A17}$$

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

$$\mathbf{P}_t^C = \min\{\mathbf{P} : \sum_{i \in s} (q_{ist}(\mathbf{P}) \times HR_{ist} \times r_{ist}) \leq \overline{E}_{st}\} \quad \forall s \in S. \tag{A18}$$

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.7 Dynamic Analysis: Optimal Investment Details

The state vector, which consists of both exogenous and endogenous variables, is an important component of our dynamic model. We discuss the evolution of the exogenous state variables in Section 5.3 so our focus here is on the endogenous state variables. The first endogenous state variable is the current BAT capacity, which is also the cumulative investment. The second state variable is the average heat rate for each strategic firm. In order to solve our model, we assume that in each time period the sum of BAT capacity across all strategic firms cannot be more than 60,000 MW and we discretize the capacity dimension of the state space using an equally-spaced fine grid with increments of 50 MW. 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. 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.

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. Therefore, BAT capacity either increases or stays at its current level. This assumption allows us to solve the model iteratively because once aggregate BAT capacity reaches 60,000 MW no firm has the incentive to invest and BAT capacity remains at this level. The value function when aggregate BAT capacity equals 60,000 MW is just $\pi/(1-\beta)$, where π is the firm's payoff at this state and β is the discount factor. We can then solve backwards for the value function along the BAT capacity dimension.

Finally, 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. 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.

A.8 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

[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.

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.

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

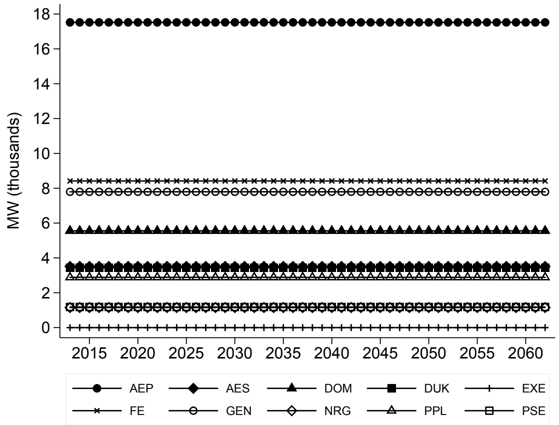
Note: The full names of the firms listed in the leftmost column are available in Table 4.

Table A5: PJM Real-Time Energy Market

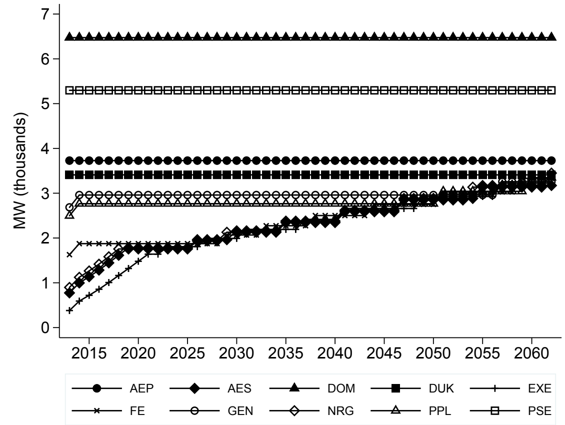
year	price	load	value
2003	$41.23	37,395	$13,506,131,646
2004	$44.34	49,963	$19,406,548,519
2005	$63.46	78,150	$43,444,335,240
2006	$53.35	79,471	$37,140,453,966
2007	$61.66	81,681	$44,119,306,030
2008	$71.13	79,515	$49,545,701,082
2009	$39.05	76,034	$26,009,558,652
2010	$48.35	79,611	$33,718,920,606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

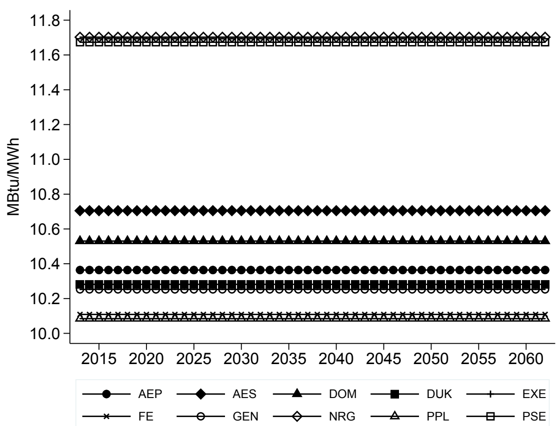
Figure A1: Paths of endogenous variables II, 2013–2062



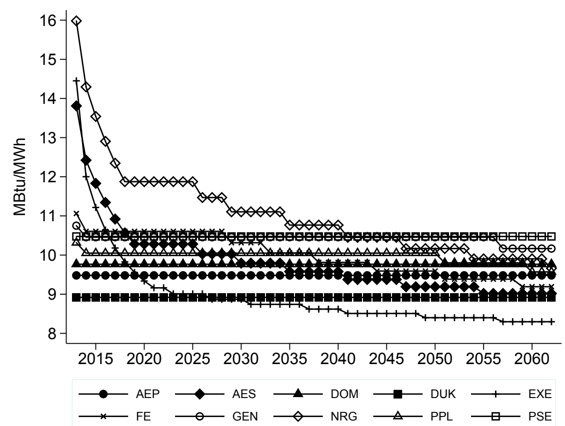
(a) coal capacity



(b) gas capacity



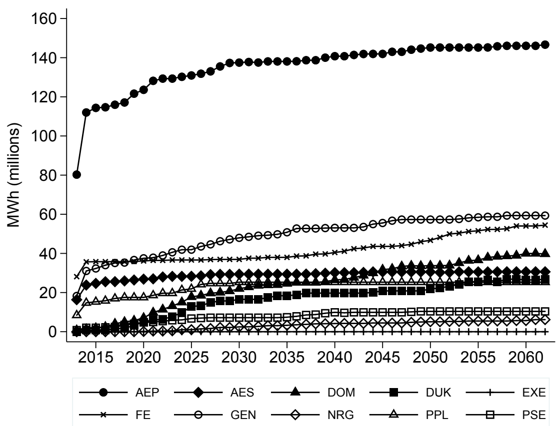
(c) coal heat rate



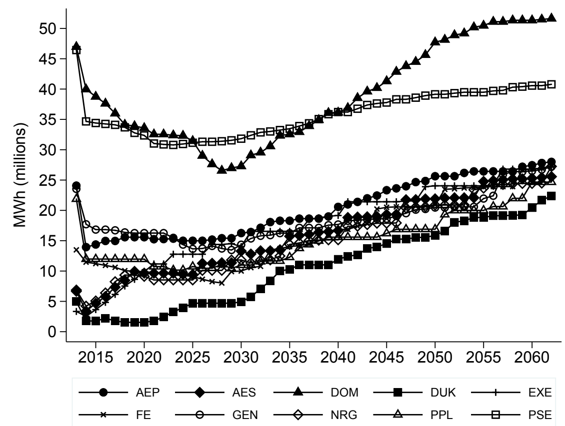
(d) gas heat rate

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.

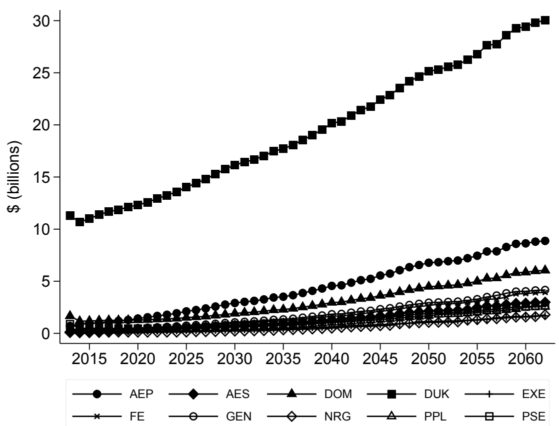
Figure A2: Paths of endogenous variables III, 2013–2062



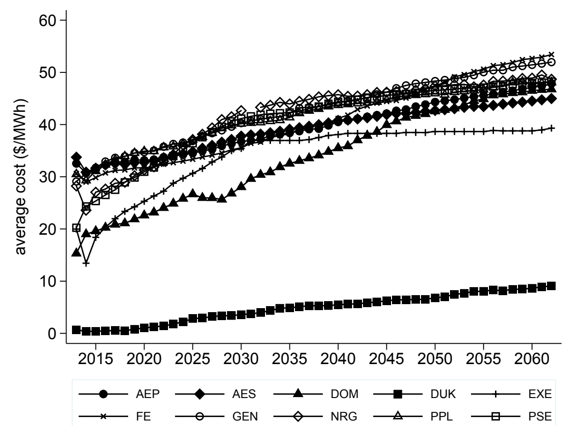
(a) coal generation



(b) gas generation



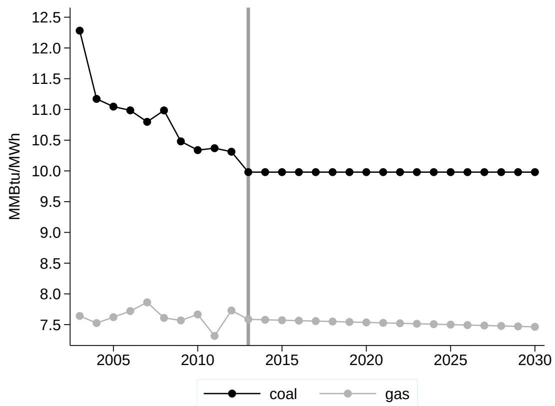
(c) profit from electricity sales



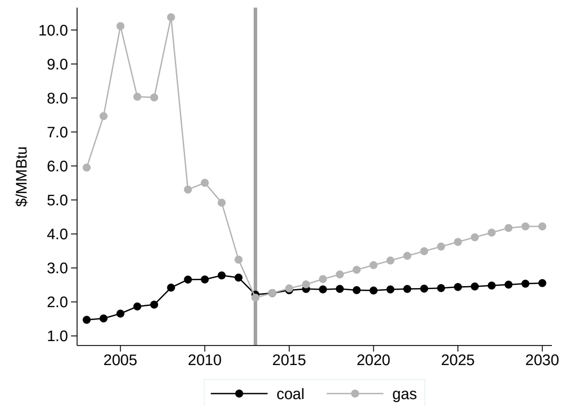
(d) cost of electricity

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.

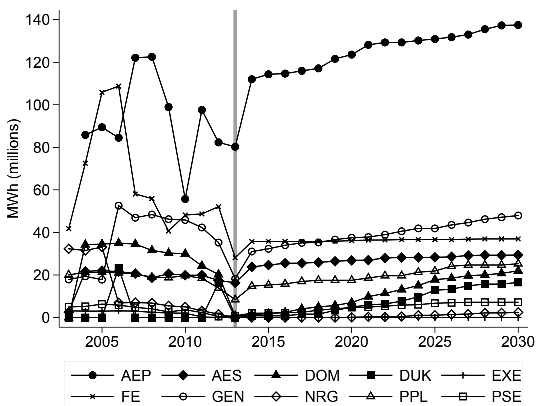
Figure A3: Data and model predictions, 2003–2030



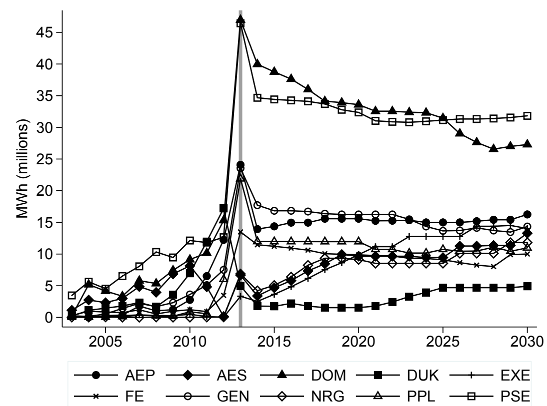
(a) BAT heat rates



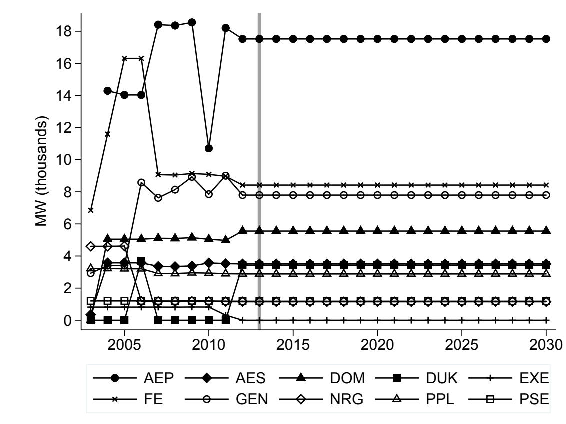
(b) fuel prices



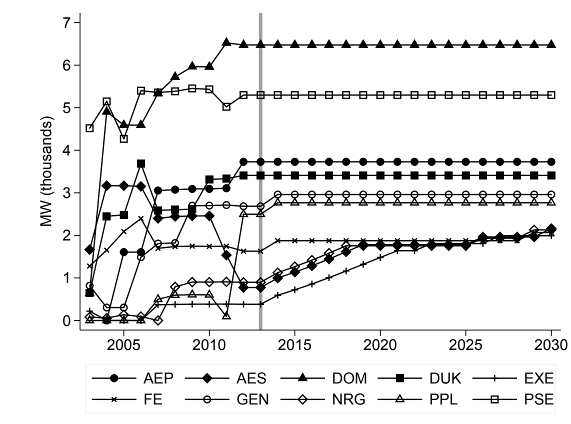
(c) coal generation



(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.