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JOSE MIGUEL ABITO, CHRISTOPHER R. KNITTEL
KONSTANTINOS METAXOGLOU, AND ANDRÉ TRINDADE

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Jose Miguel Abito Christopher R. Knittel
Konstantinos Metaxoglou André Trindade *

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Abstract

We show that inefficiencies from having separate markets to correct an 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 markets with high prices to markets with low prices. Investment in cleaner and more efficient capacity serves as an additional mechanism to reallocate output, which increases the marginal benefit of investment, and consequently improves longer-term outcomes. Using data from an integrated wholesale electricity market, we estimate a dynamic structural model of production and investment to bound the loss from separate markets for carbon dioxide emissions, and quantify the extent to which optimal investment can compensate for the loss. Despite the lack of the "invisible hand" of a single emissions market, profit-maximizing firms can play a crucial role in coordinating otherwise uncoordinated environmental regulations.

Keywords: Incomplete regulation, Investment, Emissions, Energy, Externalities.

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

*Abito: Business Economics and Public Policy Department, Wharton School, University of Pennsylvania abito@wharton.upenn.edu. Knittel: Shultz Professor of Applied Economics, Sloan School of Management, Director of the Center for Energy and Environmental Policy Research, Co-Director, Electric Power Systems Low Carbon Energy Center, MIT and NBER, knittel@mit.edu. Metaxoglou: Carleton University, konstantinos.metaxoglou@carleton.ca. Trindade: FGV EPGE Brazilian School of Economics and Finance, andre.trindade@fgv.br. We thank seminar participants at MIT, the 2nd Workshop on the Applications of Industrial Organization at McGill, UC Energy Institute at Haas, Toulouse Conference on Economics of Energy and Climate Change 2017, Cornell, HEC Montreal, Michigan, Northwestern, NYU-Stern, Wisconsin-Madison, World Bank, AEA 2017, AEA 2016, IIOC 2017, IIOC 2016, EARIE 2016, EEA 2016, and the "LCM Workshop" for useful comments. We also thank Erin Mansur for providing some of the data used in the paper, and Mushin Abdurrahman from PJM for sharing details about PJM's studies of the Clean Power Plan that helped us significantly improve the paper. Abito received funding for this project from the Kleinman Center for Energy Policy and from the Dean's Research Fund, at the University of Pennsylvania. The usual disclaimer applies.

1 Introduction

Economists have long advocated for market-based solutions to correct environmental externality problems such as harmful emissions from combustion of fossil fuels. Although a single 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. The political difficulties of organizing a single externality market raises the question to what extent having uncoordinated regulations in the form of separate markets is an adequate substitute for a single market. The main objective of this paper is to empirically address this question by examining the relative economic efficiency of single versus separate externality markets, and understanding the mechanisms that drive their relative efficiencies.

Our work is motivated by two recent examples of failures in coordinating environmental policies across jurisdictions. The first is the current legal and political challenge to the U.S. Clean Power Plan (CPP), a federal regulation put forward by the Obama administration setting carbon dioxide (CO_2) emissions limits from electric power plants for 2022–2030. Although the intention of the Obama administration was the introduction of a comprehensive policy to combat climate change at the federal level, the exact design and implementation of CO_2 regulation will ultimately be at the state level.[1] A second example of a potential failure to coordinate policies across jurisdiction is the withdrawal of the UK from the European Union (EU). What has now become known as *Brexit* may lead to the UK's departure from the European Union Emissions Trading System (EU-ETS) as well, and force the country to create its own market for CO_2 emissions.[3]

The paper's main contribution is to show both theoretically and empirically that the organization of the product market can effectively coordinate uncoordinated regulation of the externality.[4] Facing an integrated product market, multi-plant firms make output decisions

[1]There are two reasons why CO_2 regulations are likely to be at the state level. First, the Clean Air Act only authorizes the U.S. Environmental Protection Agency (EPA) to set targets at the state level and solicit state implementation plans to achieve these targets. Second, on October 10, 2017, the Trump administration submitted a proposal to repeal the CPP that may delay or even terminate efforts to regulate CO_2 emissions at the federal level.[2] If the second and less optimistic scenario materializes, any regulation of CO_2 emissions will most likely be a state-level effort.

[3]Not surprisingly, discussions regarding the type of policies that the UK may implement following its 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)).

[4]Existing work on externality markets has mainly focused on quantifying the gains from emissions permit trading—for example, Bui (1998) and Carlson et al. (2000)—and has ignored the role that the product market can play in coordinating regulations across different jurisdictions.

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. In a frictionless environment, output reallocation and externality price readjustment will lead to convergence of externality prices, as if there were a single externality market.[5] In practice, frictions such as capacity constraints exist, and prevent perfect reallocation of output and readjustment of externality prices, hence creating an efficiency wedge between single and separate externality markets. The size of this wedge is an empirical question.

The backbone of our empirical analysis is a dynamic structural model of production and investment, which we use to simulate firm behavior with single and separate externality markets. We use data from the Pennsylvania-New Jersey-Maryland (PJM) wholesale electricity market and consider CO_2 emissions regulation implemented through the Clean Air Act. PJM operates the world's largest wholesale electricity market covering all or parts of 13 states (Figure 1). With state-by-state implementation (separate CO_2 markets), emissions in each state cannot exceed their respective state-level targets. In contrast, with regional implementation (single CO_2 market), states in PJM can pool their targets and comply as a region. Thus, with state-by-state implementation, firms operating power plants across the PJM region face different CO_2 (shadow) 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.

In our model, firms own several plants with different capacities located in different states. Plant-level differences in capacity, age, technology, and location affect the overall cost of electricity generation. In each period, firms produce electricity using their existing plants, which they sell to the PJM wholesale electricity market. Although the wholesale electricity

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.

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 these regulations across jurisdictions (Abito et al., 2017). Unlike markets for externalities—which, by nature, have to be created and organized by multiple *public* institutions—product markets are easier to organize given that markets for these goods are already established. Moreover, product markets often extend multiple jurisdictions since *private* entities are not tied to a specific jurisdiction unlike public agencies.

[5]This idea is reminiscent of Samuelson (1948)'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.

market is modeled as competitive as in Bushnell et al. (2008), we allow investment decisions to be strategic and forward-looking (Dixon, 1985). That is, firms may take into account their rivals' reactions to their investment decisions, as well as the effect of investment on future market outcomes. 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.

To effectively capture firms' supply decisions and incentives to invest in response to the regulatory environment they face, we need a model that preserves the heterogeneity of costs across plants *and* tracks their evolution as firms invest in new capacity. Plant costs depend on a number of factors: efficiency (heat rate), emission rates for various pollutants and associated compliance costs, fuel prices, and other operations-and-maintenance (O&M) costs. As a result, a high-dimensional state vector is required to track the evolution of all these factors for the existing plants and the new capacity in which firms invest in.[6]

Incorporating a rich stage game within a dynamic model is computationally challenging. Our approach in addressing this challenge is novel and is based on the observation that new capacity will be infra-marginal in the wholesale electricity market, at least in the medium run. As we explain later, because of the infra-marginal nature of new capacity, it suffices to keep track of the average heat and emission rates of cumulative investment over time. As a result, we substantially reduce the dimension of the state vector, which significantly alleviates the computational burden for our structural model while still incorporating the rich information on plants' costs.

We estimate our model by first *directly* computing the cost of producing electricity using data on fuel prices and compliance costs, along with plant-level data on heat rates, emission rates, and O&M costs as in Mansur (2007) and Bushnell et al. (2008), as well as estimating the demand for electricity. We then estimate investment costs using the two-step approach in Bajari et al. (2007) similar to 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. The production costs, along with demand and investment cost estimates allow us to predict supply and investment decisions. Using our estimates, we solve a series of dynamic investment problems to simulate outcomes with a single and with separate CO_2 markets.

[6] The literature has so far employed low-dimensional approximations of cost functions and a small number of technologies to ease the computational burden. For example, Bushnell et al. (2008) use piece-wise linear approximations to the firms' cost functions to study static competition and market power in different U.S. wholesale electricity markets. Bushnell and Ishii (2007) add investment to the model of Bushnell et al. (2008) but restrict the state space by assuming 5 different choices of plant types (capacity and technology). PJM (2016) compares regional and state-by-state implementation of the environmental regulation and assumes existing and new electric generating units are also limited to a small number of technologies. More importantly, the PJM report treats investment as exogenous.

We use the model and the estimated primitives to simulate the effects of environmental regulation that caps CO_2 emissions. In all the scenarios considered, we assume that CO_2 regulation is implemented through a market mechanism which gives rise to CO_2 prices. An equilibrium in our model is a sequence of CO_2 prices and wholesale electricity prices that clear both markets simultaneously. Our main interest lies in the comparison of outcomes with a single CO_2 market to outcomes with separate CO_2 markets. In the former case, there is PJM-wide CO_2 price. In the latter case, the CO_2 prices are state specific.

We start our welfare analysis by computing an upper bound on the static cost inefficiency from separate CO_2 markets. In computing cost, we treat capacity as fixed and exogenous, but allow firms to reallocate output given the existing portfolio of plants. This analysis is static because we compare cost with a single and separate CO_2 markets for each value of the state variable, that is, new capacity arising from investment. We find that for low levels of new capacity, it is not feasible to meet both PJM-wide and state-level targets, and so costs end up being identical. On the other hand, for high levels of new capacity, the state-level targets no longer bind, which implies a zero CO_2 price for both single and separate markets. In this case, costs are also identical. Only for intermediate levels of new capacity do costs with single and separate markets diverge. For these levels, we find that the difference in cost is at most \$1.8 billion, or about 35% of the cost of compliance with the CO_2 regulation.

Next, we examine the role of investment as an additional mechanism to reallocate output. In this case, we examine how different assumptions regarding firm behavior, from full coordination of investment across firms to non-strategic investment, affects the optimal level of investment under the two regulatory regimes. We find that across all assumptions regarding investment behavior, investment incentives are stronger with separate markets compared to a single market. Intuitively, with separate markets, firms do not have the option to "buy emissions" from plants facing lower CO_2 prices. As a result, higher CO_2 compliance costs inflate plants' cost of generating electricity which increases the reward to investing in cleaner and more efficient capacity. Although in the short-run electricity prices go up due to the inability to trade across CO_2 markets, more investment allows the electricity market to transition to a steady state that has a larger share of cleaner and more efficient capacity. Hence, static inefficiencies resulting from separate markets are significantly—and in some cases, completely—mitigated.

Our paper is related to several literatures. First, our work 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) 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 equilibrium framework and two-step estimation method, although we depart from their approach in that we do not need to estimate costs but instead compute 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)). 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. However, our research question and focus are completely different.[7]

Finally, the 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 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, which has only received limited attention (e.g. Bushnell and Ishii (2007)).

The remainder of the paper is organized as follows. In Section 2, we provide background on the PJM wholesale electricity market and CO_2 regulation under the Clean Air Act. We then 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

[7]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 that of investment.

markets for an externality in Section 3. 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. Additional details regarding the data, our empirical analysis, the heterogeneity of investment costs in our model, and the emissions' market clearing algorithm are provided in a separate Online Appendix.

2 Background

2.1 The 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 across 20 zones (Figure 1). Its wholesale electricity markets began operation in 1997. PJM coordinates the buying, selling and delivery of wholesale electricity through its Energy Market. As the market operator, PJM balances the needs of buyers, sellers and other market participants and monitors market activities to ensure "open, fair and equitable access."[8] To give the reader about the size of the transactions in PJM, between 2003 and 2012, the value of its real-time energy market grew from approximately $13 billion in 2003 to $26 billion in 2012 (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] The 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%. The two fuels combined account, on average, 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 the total capacity.

Figure 2 shows that the monthly average electricity prices track closely the gas price paid

[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.

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 one we see in coal prices for the entire country.

2.2 The Clean Power Plan

On August 3, 2015, the U.S. Environmental Protection Agency (EPA) finalized two sets of rules aiming to address CO_2 emissions from fossil-fired power plants (EPA (2015)). Fossil fuel-fired plants, which are mostly coal- and gas-fired, are the largest source of CO_2 emissions, accounting for about a third of U.S. total greenhouse gas emissions. The first set of rules addresses emissions from existing sources, while the second set of rules pertains to new, modified, or reconstructed sources.

The EPA has the authority to regulate existing and new sources under the federal-level Clean Air Act. In this paper, we will collectively call the two sets of rules as the Clean Power Plan (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] Thus, unlike the applicable rule for existing sources which is a statewide limit, the rule for new sources is source- or unit-specific. Although the EPA cannot prescribe a particular technology, the emission limits set by the EPA essentially preclude technologies that cannot meet the limit. For example, the final rule specifies a limit of 1,000 lbs of CO_2 per MWh for gas-fired plants, which can only be achieved by the latest combined-cycle technology. For coal-fired plants, the limit is 1,400 lbs of CO_2 per MWh

[10]Units that are built, modified or reconstructed after the prevailing Section 111(d) targets were set will be classified as "new" as long as the same targets are in place. For example, in our setting 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.

which is currently only achievable with carbon capture and storage technology, a technology that is costly and not widely available.

The CPP calls for a 32% reduction in CO_2 emissions from the power sector by 2030 relative to its 2005 levels. It aims not only to reduce emissions that cause harmful soot and smog, but also to promote clean energy innovation, development and deployment, and lay the foundation for a long-term strategy to tackle climate change with estimated net benefits of \$26–\$45 billion. The Plan establishes interim and final rate-based (lbs./MWh) and mass-based (short tons) state goals regarding CO_2 emissions. The interim goals are for the period 2022–2029, while the final goals are for 2030. The Plan also establishes 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 gives the states the flexibility to develop and implement plans that ensure that power plants in their state—either individually, together, or in combination with other measures—achieve the interim and final goals.

To set these targets, the EPA determined the best system of emission reductions (BSER) that has been demonstrated for a particular pollutant and particular group of sources by examining technologies and measures previously used. The BSER consists 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

[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 has a different goal based upon its own particular mix of different sources.

and Pennsylvania are 92.1 and 110.2. 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).

3 Simple Model of CO_2 Markets

A regional (PJM-wide) CPP implementation can take advantage of state heterogeneity leading to potentially large gains from trade. However, participating states have to be willing to coordinate in the design and implementation stages. In this section, we illustrate the inefficiencies that arise with a state-by-state implementation and how a single product market—the wholesale electricity market—can mitigate these inefficiencies. We also examine the role of investment as the main mechanism for coordinating compliance across states.

For the purpose of illustration, we make a series of assumptions to build a stylized model. First, there are only two states in PJM, say s and s'. Additionally, there is a single electricity-generating firm. The firm produces quantities q_s and $q_{s'}$ of electricity in plants located in state s and s', respectively, which correspond to MWh of electricity.[12] The firm can reduce its CO_2 emissions in state s (s') by an amount a_s ($a_{s'}$). The firm's total cost function is given by $C(q_s, q_{s'}, a_s, a_{s'})$. 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. The implied mass-based targets are $\overline{Q}_s$ and $\overline{Q}_{s'}$. Regional compliance requires:

$$(q_s - a_s) + (q_{s'} - a_{s'}) \leq \overline{Q}_s + \overline{Q}_{s'}. \tag{1}$$

State-by-state compliance requires:

$$q_s - a_s \leq \overline{Q}_s \tag{2}$$
$$q_{s'} - a_{s'} \leq \overline{Q}_{s'}. \tag{3}$$

The firm chooses electricity generation and emissions reduction for each state in order to maximize its profit given by:

$$\pi = p \times (q_s + q_{s'}) - C(q_s, q_{s'}, a_s, a_{s'}), \tag{4}$$

[12] We assume that each power plant has a single electric generating unit. In reality, power plants may have more that one unit.

subject to either the regional or state-by-state compliance.

Single market for the externality: With regional compliance, emissions in either state face the same shadow price, λ. Thus, at the optimum, the marginal cost of reducing emissions across the two states will be equal to λ:

$$\frac{\partial C}{\partial a_s} = \frac{\partial C}{\partial a_{s'}} = \lambda. \tag{5}$$

Combining the first-order conditions with respect to emissions reductions with the first-order conditions with respect to output, we have:

$$p = \frac{\partial C}{\partial q_s} + \frac{\partial C}{\partial a_s} = \frac{\partial C}{\partial q_{s'}} + \frac{\partial C}{\partial a_{s'}}, \tag{6}$$

which implies:

$$\frac{\partial C}{\partial q_s} = \frac{\partial C}{\partial q_{s'}}. \tag{7}$$

Separate markets for the externality: With state-by-state compliance, the marginal cost of reducing emissions need not be equal, unless the shadow prices across the two states are equal. Nevertheless, the sum of the marginal cost of reducing emissions and producing electricity for each state are both equal to the electricity price according to (6). Therefore, production and emissions reductions are reallocated across the two states. This reallocation, however, is not necessarily as efficiently as in the single market case.

Consider the special case where electricity generation can be perfectly reallocated across states. With perfect reallocation, total cost takes the following form:

$$C(q_s, q_{s'}, a_s, a_{s'}) = C(q_s + q_{s'}, a_s, a_{s'}). \tag{8}$$

In this case, we have $\partial C/\partial q_s = \partial C/\partial q_{s'}$. Since (6) still holds, we have $\partial C/\partial a_s = \partial C/\partial a_{s'}$. Hence, state-by-state compliance leads to the same outcome as regional compliance.

The previous example shows that the extent to which the inefficiencies from separate markets for the externality are mitigated depends on the ability to reallocate output across states. In practice, however, there are frictions that limit this ability. First, the extent of reallocation depends on the capacity of existing plants in these states. Although it may be cheaper to produce output in state s as opposed to state s' due to a higher CO_2 permit price in the latter, the firm is limited by the available capacity in s'. Thus, investment in new capacity is an important mechanism that facilitates output reallocation. Second, there are multiple competing firms, which may not be able to coordinate investment in the same way as a single-agent or a planner. Thus it will be important to capture the investment incentives of competing firms.

Investment facilitates reallocation because new capacity replaces old capacity, and part of the investment decision is the location of the plant. While the location decision is important in general, it is not relevant for our paper as long as new sources are to be treated differently under the CPP. In essence, new capacity is located in a state with a zero CO_2 permit price, conditional on the new capacity meeting the source-specific emissions standard (Section 111(b) of the Clean Air Act). The fact that new capacity faces a zero CO_2 permit price and adopts the best available technology is important in mitigating the negative effects of having separate markets for emissions as opposed to a single market. Notably, the role of investment as an implicit production reallocation mechanism shows the importance of the dynamic component of our empirical model, which would be ignored in a static approach.

Investment incentives: Figure 3 provides an example where wholesale electricity prices are actually higher with regional than state-by-state CPP implementations, and consumer surplus and profits are higher with the state-by-state implementation. This example shows the stronger incentives to invest with state-by-state implementation.

As it was the case earlier in this section, we make a series of assumptions for the purpose of illustration. Electricity demand is fixed at 3 MWh. There are three existing plants owned by a single price-taking firm.[13] The first plant is located in state s' and can produce 1 MWh of electricity at a marginal cost of \$20/MWh. The other two plants are located in state s. Each of the two plants can produce 1 MWh of electricity. However, the two plants have different marginal costs, which are \$30/MWh and \$20/MWh, respectively. Suppose also that the firm can add capacity that produces 1 MWh of electricity at a marginal cost of \$10/MWh. This new capacity is not subject to emissions regulation—faces a permit price of 0—regardless of its location and represents the best available technology. Finally, let $\Gamma > 0$ be the fixed cost of investment.

The three panels of Figure 3 show the wholesale electricity market equilibrium for three possible scenarios: no CPP implementation (panel (a)), regional CPP implementation (panel (b)), and state-by-state CPP implementation (panel (c)). The left part of each panel shows the equilibrium without investment while the right part shows the equilibrium with investment.

In the absence of CPP, investment lowers wholesale prices from \$30/MWh to \$20/MWh

[13] We maintain the assumption that each plant has a single electric generating unit.

because the least efficient plant, which was marginal prior to the investment, no longer supplies output. This reduces variable profits from \$20/MWh to \$10/MWh, and, therefore, the firm does not have an incentive to invest.

Next, with regional implementation, existing plants in both s and s' face a single CO_2 permit price such that the marginal cost for these plants increases by \$10. Without investment, wholesale price increases to \$40/MWh and profits are equal to \$20. With investment, wholesale price goes up to \$30/MWh and profits are equal to $\$20-\Gamma$. Although the variable profit with investment is higher with state-by-state implementation than in the absence of CPP, it is still not enough to attract investment for any $\Gamma > 0$.

Finally, with state-by-state implementation, existing electric plants in state s' face an increase of \$5 in their marginal cost, while the existing plants in state s face an increase of \$15 in their marginal cost due to the higher CO_2 permit price in s. Wholesale price increases to \$45/MWh without investment, but goes down to \$35/MWh with investment. With state-by-state implementation, the firm will invest as long as $\Gamma < 5$. In this case, wholesale prices with regional and state-by-state implementations are \$40 and \$35 respectively, while consumer surplus and profits are higher in the latter.

Although the model is admittedly stylized, it highlights the possibility of mitigating inefficiencies with separate markets via investment. It also highlights the fact that market outcomes depend on a series of factors, such as the portfolio of plants, the marginal plant setting the market clearing price, and investment costs. Therefore, one needs to capture effectively these factors in order to properly assess the relative merits of alternative policies considered.

4 Empirical Model

We model supply and investment decisions of firms participating in the PJM wholesale electricity market. The number of strategic firms, N, is smaller than the total number of firms participating in the market due to the presence of the competitive fringe. Supply decisions—selling electricity to the wholesale market—are monthly. Investment decisions are annual. At the beginning of the year, the strategic firms decide on investment in either coal- or gas-fired capacity, which becomes available the following year. At beginning of each month, all firms decide on how much electricity to sell in the wholesale market subject to their capacity constraints.

In what follows, we discuss the details of our model. We first discuss supply and demand in

PJM wholesale market, followed by our investment model. We complete our discussion by formally defining the Markov Perfect Equilibrium of the dynamic game. Figure 4 provides an overview of the timing of the model.

4.1 Wholesale Electricity Market

To model firm behavior in the wholesale electricity market, we build on the results in Wolak (2000) and Bushnell et al. (2008)—henceforth BMS. Wolak and BMS show that electricity markets in the presence of forward contracts, as is the case for PJM, generate outcomes that are much closer to those from a competitive setting than to those from a Cournot game.[14] Therefore, we implement our model as if firms were price-takers producing electricity subject to capacity constraints.[15] 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. Table 4 provides a list of the strategic firms we consider noting that we aggregate subsidiaries to holding companies.

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. 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.

Given our implementation of the stage game as a competitive market, supply is fully determined by the marginal cost of electricity. Following BMS and Mansur (2007), the marginal

[14] 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 contracts are not as straightforward to deal with as in BMS because of the dynamic nature of the model. We also implicitly assume that the effect of the forward contracts on the competitive nature of the market remains the same in the future. Overall, modeling forward commitments is beyond the scope of the paper.

[15] 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.

cost of generating electricity (\$/MWh) for plant i at time t is given by:

$$c_{it} = VOM_{it} + HR_{it} \times \left(P_t^f + P_t^s r_{it}^s + P_t^n r_{it}^n \right), \tag{9}$$

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 (9) 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.

Market supply is determined by ordering all available capacity in terms of its marginal costs as shown in Figure 5. This merit order along the supply curve dictates the sequence in which the various sources are dispatched as the demand for electricity increases. The equilibrium wholesale price is the marginal cost of the most expensive source called to serve demand. Given fuel and emissions permit prices, the market supply function is a step function described by the pair (K, c), where K is the capacity with marginal cost less than or equal to c. Because we observe all of the components in (9), we can construct this step function directly from the data.

To model demand, we adapt the approach in BMS using monthly data and a more parsimonious specification. The need for parsimony stems from the fact that we use 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 strategic firms. 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:

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

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 (10) as follows:

$$\widehat{q}_\tau^{fringe} = \widehat{\lambda}_\tau + \widehat{\beta} ln(p_\tau^w) \tag{11}$$

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

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

$$Q_\tau^S = Q_\tau - \widehat{q}_\tau^{fringe} = Q_\tau - \widehat{\lambda}_\tau - \widehat{\beta} ln(p_\tau^w) \tag{13}$$

Finally, we write:

$$Q_\tau^S = \widehat{a}_\tau - \beta ln(p_\tau^w), \quad \widehat{a}_\tau \equiv Q_\tau - \widehat{\lambda}_\tau. \tag{14}$$

4.2 Investment

Firms' investment decisions are fuel-specific, costly, and affect capacity with implications for the shape of the marginal cost function. Investment in coal- and gas-fired capacity is endogenous. We assume firms invest in the best available technology (BAT), which is the technology with the lowest heat rate (hr) at the time of investment. This assumption, which is motivated by the Carbon Pollution Standard (CPS) under Section 111(b) of the Clean Air Act, allows us to make our model tractable by reducing the number of state variables that we need to track over time to calculate profits in the electricity market. Although we assume investment in BAT technology, investment in technology that leads to inframarginal capacity is sufficient for the validity of our approach.

Figure 6 illustrates how the BAT assumption helps us to address the dimensionality problem. The two lower steps of the supply curve in panels (a) and (b) 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.

Using $f \in \mathscr{F} = \{coal, gas\}$ to denote the fuel, let i_{jt}^{f} 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:

$$\underline{K}_{jt+1} = \underline{K}_{jt} + i_{jt}^{coal} + i_{jt}^{gas}. \tag{15}$$

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:

$$\underline{S}_{jt+1} = \frac{\underline{S}_{jt}\underline{K}_{jt} + i_{jt}^{gas}}{\underline{K}_{jt+1}}. \tag{16}$$

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:

$$\underline{HR}_{jt+1}^{gas} = \frac{\underline{S}_{jt}\underline{K}_{jt}}{\underline{S}_{jt}\underline{K}_{jt} + i_{jt}^{gas}}\underline{HR}_{jt}^{gas} + \frac{i_{jt}^{gas}}{\underline{S}_{jt}\underline{K}_{jt} + i_{jt}^{gas}} hr_{jt}^{gas}, \tag{17}$$

where hr_{jt}^{gas} 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:

$$\underline{c}_{jt} = (1 - \underline{S}_{jt})\underline{c}_{jt}^{coal} + \underline{S}_{jt}\underline{c}_{jt}^{ng} \tag{18}$$

where $\underline{c}_{jt}$ is computed using (9) noting that there are fuel-specific components entering the equation.

By construction, BAT capacity is infra-marginal, at least in the medium term. Moreover, 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.[16] 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 $(K_{-jt} + i_{jt}^{gas}, c_{-jt})$, that is a horizontal shift equal to the amount of investment. This example is illustrated in panel (b) of Figure 5.

[16]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.

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. Furthermore, $C(q_{jt}, \mathbf{s}_t)$ is the total cost for producing q_{jt} when the state vector is $\mathbf{s}_t$. Using p_t^w to denote the equilibrium wholesale electricity price and ν_{jt} to denote a private shock that is IID across firms and time drawn from a common distribution $G_\nu = (0, \sigma_\nu^2)$, the per-period profit is given by:

$$\pi_{jt}(\mathbf{a}_t, \mathbf{s}_t, \nu_{jt}) = \overline{\pi}_{jt}(\mathbf{a}_t, \mathbf{s}_t) - \Gamma_{jt}(\mathbf{a}_t, \nu_{jt}) \tag{19}$$

with the profit function excluding investment cost being:

$$\overline{\pi}_{jt}(\mathbf{a}_t, \mathbf{s}_t) = p_{jt}^r \times q_{jt}^r + p_t^w \times (q_{jt} - q_{jt}^r) - C(q_{jt}, \mathbf{s}_t). \tag{20}$$

The investment cost is given by:

$$\Gamma_{jt}(\mathbf{a}_t, \nu_{jt}) = \sum_{f \in \mathscr{F}} (\gamma^f + \nu_{jt}^f) i_{jt}^f \tag{21}$$

The specification for the static profit function in (20) allows for retail sales q_{jt}^r at a price p_{jt}^r that are assumed to be sunk at the time production decisions are made for the wholesale markets.

Although i_{jt}^f in (21) represents only *positive* adjustments to capacity, our model allows for capacity reductions (divestments) as well. However, unlike Ryan (2012) or Fowlie et al. (2016), we do not need to introduce a scrap value associated with reductions in capacity.[17] This is due to specificities in our model. In fact, to be consistent with our BAT assumption—all new investment is in units that face the lowest costs and are located in the leftmost segment of the supply curve—all divested units need to be located in the rightmost segment of the supply curve. In other words, divestment only affects the least efficient coal units, which in our model have a cost above the equilibrium price and are extramarginal (idle) anyway. Scrapping older units or keeping them idle does not have an impact on the equilibrium price. Hence, we can separate divestment decisions from the ones associated with generation and BAT investment.[18]

[17]A version of (21) with scrap value would be $\Gamma_{jt} = \sum_f 1_{[i_{jt}^f > 0]}(\gamma_1^f + \nu_{1jt}^f) i_{jt}^f + 1_{[i_{jt}^f < 0]}(\gamma_2^f + \nu_{2jt}^f) i_{jt}^f$ as in Ryan (2012).

[18]Firms could, potentially, take into account future scrap values of BAT investment when they decide to build new capacity. However, as the lifecycle of a power plant is typically several decades, the present value

4.2.1 Capacity Markets

The idea behind the capacity market is that there are 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 auctions in the PJM capacity market.

Although PJM does operate a capacity market and we do not explicitly model capacity payments, our setup can accommodate 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%.[19]

of scrappage at the time of construction would be very small. Therefore, and to keep the model simple, we assume that new units operate forever.

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

4.3 Markov Perfect Equilibrium

We now define the notion of equilibrium in our model given a vector of actions $\mathbf{a}_t = \{a_{jt}\}_{j=1}^{N}$. In particular, the state vector is:

$$\mathbf{s}_t = \left(\alpha_t, \mathbf{p}_t^F, \{\underline{K}_{jt}, \underline{S}_{jt}, \underline{HR}_{jt}^{coal}, \underline{HR}_{jt}^{ng}\}_{j=1}^{N}\right). \tag{22}$$

The endogenous part of the state vector that relates to BAT capacity investment and its evolution is discussed in the previous section. In terms of the exogenous state variables, α_t is the intercept of the inverse residual monthly demand for electricity and $\mathbf{p}_t^f$ is a vector of monthly coal and gas prices.[20] The future path of the exogenous state vector is allowed to exhibit some uncertainty, which can affect the investment decisions.

Each firm's behavior is Markovian and depends only on the current state and private shock as in Ericson and Pakes (1995). Hence, a Markov strategy for firm j, σ_j, will map the state and private shock into actions. The profile $\boldsymbol{\sigma}$ is a Markov Perfect Equilibrium (MPE) if each firm j's strategy σ_j generates the highest value among all alternative Markov strategies σ_j^l given the rivals' profile $\boldsymbol{\sigma}_{-j}$:

$$V_j(\mathbf{s}; \boldsymbol{\sigma}) \geq V_j(\mathbf{s}; \sigma_j^l, \boldsymbol{\sigma}_{-j}), \tag{23}$$

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

$$V_j(\mathbf{s}; \boldsymbol{\sigma}) = \sum_{t=0}^{\infty} E\left[\pi_{jt}(\mathbf{a}_t, \mathbf{s}_t, \nu_{jt})|\mathbf{s}_0\right]. \tag{24}$$

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

[20] 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.

of the state variables. The advantage of this approach is that the primitives can be estimated without the need to solve for an equilibrium even once. 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:

$$K_{jt+1} = \begin{cases} K_{jt}, & T(K_{jt}) - B(K_{jt}) < K_{jt} < T(K_{jt}) + B(K_{jt}) \\ T(K_{jt}), & \text{otherwise.} \end{cases} \tag{25}$$

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

$$T(K_{jt}) = \lambda_1^T \mathbf{1}_{[entrant],jt} + \lambda_2^T K_{jt} + \lambda_3^T \mathbf{K}_{-jt} + \lambda_4^T \mathbf{P}_t + \varepsilon_{jt}^T \tag{26}$$

$$B(K_{jt}) = \lambda_1^B + \lambda_2^B K_{jt} + \varepsilon_{jt}^B. \tag{27}$$

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_{jt}^T and ε_{jt}^B.

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

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 $\mathbf{W}_j(\mathbf{s}; \sigma_j^l, \boldsymbol{\sigma}_{-j})$ 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 $\{\sigma_j^l\}_{l=1}^L$ and using σ_j^0 to denote the observed policy, we want to estimate $\mathbf{W}_j(\mathbf{s}; \sigma_j^l, \boldsymbol{\sigma}_{-j}^0)$ 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:

$$\widehat{\mathbf{W}}_j(\mathbf{s}; \sigma_j^l, \boldsymbol{\sigma}_{-j}^0) = \sum_{t=1}^{N_T} \beta^t \left(\overline{\pi}_{jt}^l(\mathbf{a}_t, \mathbf{s}_t) - \Gamma_{jt}^l((\mathbf{a}_t, \nu_{jt}))\right). \tag{28}$$

We rewrite the MPE condition (23) for the lth alternative policy as follows:

$$g_{j,l}(\theta) = \left[\widehat{\mathbf{W}}_j(\mathbf{s}; \sigma_j^l, \boldsymbol{\sigma}_{-j}^0) - \widehat{\mathbf{W}}_j(\mathbf{s}; \sigma_j^0, \boldsymbol{\sigma}_{-j}^0)\right] \cdot \theta \tag{29}$$

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.4, 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 minimized:

$$\min_{\theta} \; Q(\theta) = \frac{1}{NL} \sum_{j=1}^{N} \sum_{l=1}^{L} \mathbf{1}\left\{g_{j,l}(\theta) > 0\right\} g_{j,l}(\theta)^2. \tag{30}$$

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 4.1, 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/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. The slope of the residual demand is held constant at the mean value estimated as detailed above.

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

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]

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

[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.

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 \$1.1 million per MW 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%

[25] All dollars are nominal.

(panel (e)). After 20 years of growth of the share of coal in electricity generation that peaks at 40%, we see slight a decline to 37% in the later years. The share of sources other than coal and gas in electricity generation decreases from 52% in 2013 to 33% 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 11,000 MW of gas-fired capacity. Three firms account for roughly 3/4 of the total investment. Exelon accounts for 2,800 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 noting that our model is not flexible enough to allow for on- and off-peak prices.[26] As we can see, our model tracks well the NYMEX futures prices outside the September-February window.[27]

6 Welfare with Single versus Separate Markets

6.1 Overview

To compare market outcomes with single and separate CO_2 markets, we assume 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.

[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 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.

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 in dollars per short ton that clears the permit market. 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 corresponds 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 or merit order of the wholesale electricity market. This additional cost is different for sources with different emission rates (lbs./MMBtu). Hence, we compute the marginal cost for source i in state s at time t as follows:

$$c_{ist}^{C} = c_{ist} + P_{st}^{C} \times r_{ist}^{C} \times \zeta, \tag{31}$$

where c_{ist} is the generation cost excluding the cost of emissions ($/MWh), P_{st}^{C} is the CO_2 price ($/ton), r_{ist}^{C} is the emissions rate (lbs./MMBtu), and ζ is an appropriate scaling factor to take into account units of measurement. In the case of a single market, $P_{st}^{C} = P_{t}^{C}$, $\forall s \in S$, where S is the set of the 11 PJM states listed in Table 2.

All else equal, the CO_2 price changes the merit order of the various generation sources and increases the cost of producing 1 MWh of electricity. Equilibrium demand and supply in the wholesale electricity market determine the sources that are called to serve demand and the level of emissions. The level of emissions and the emissions target in turn determine 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 market-clearing algorithm in Section A.5.

We explore market outcomes in a series of alternative investment scenarios subject to regulations consistent with the Clean Air Act. In exploring these market outcomes, we make a series of assumptions, four of which are discussed here. 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, capacity post-2012 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 $50 for the CO_2 price and set the

[28] See discussion on exogenous state variables in Section 5.3.

[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

post-2030 CPP targets at their 2030 levels.[30]

The discussion that follows sheds light to the implications of production reallocation and investment for a series of economic and environmental outcomes of interest. We start by exploring market outcomes treating investment as exogenous. This analysis provides us with a bound on the static welfare losses associated with separate markets. We then explore outcomes for scenarios with optimal investment. An overview of our findings is available in Table 9.

6.2 Static Analysis

Our first objective is to showcase the role of output reallocation in mitigating the inefficiencies with separate markets in the presence of an integrated product market. We compare the cost of producing electricity with single and separate CO_2 markets treating investment in BAT capacity as given. Specifically, we solve for the equilibrium of the electricity and CO_2 market(s) for BAT capacity levels between 0 and 60,000 MW for 2030, noting that the qualitative nature of our findings is similar for all years between 2022 and 2030.

In Figure 12, we plot electricity production cost with single and separate CO_2 markets as a function of BAT capacity. As can be readily seen from the graph, there is practically no difference in cost between single and separate CO_2 markets for high and low levels of BAT capacity. The wedge in cost only exists in intermediate levels of BAT capacity.

In the case of high BAT capacity levels—largely, in excess of 43,000 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 \$50 even with a single market are needed to meet the targets.

Costs between single and separate markets only diverge for intermediate BAT capacity levels.

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.

The largest difference is about \$1.79 billion at BAT capacity of 29,000 MW. This difference is about 35% of CPP compliance cost which is computed by taking the difference in electricity generation and investment cost with and without the CPP, assuming a regional market.

There are two takeaways from the static analysis. First, the level of BAT capacity is an important determinant of the relative efficiency between single and separate CO_2 markets. Given the importance of BAT capacity, we explore optimal investment in the next section. Second, our static analysis provides an upper bound of the cost inefficiency of separate CO_2 markets, which illustrates to what extent an integrated product market can be an effective alternative to coordinating CO_2 emissions regulations.

6.3 Optimal Investment

Our next objective is to examine the implications of investment for market outcomes when investment is a result of optimizing behavior. We first consider the case of firms using investment strategically. We then consider two extreme cases of optimal investment behavior–one where investment is chosen to maximize industry profits, and one where investment is chosen to maximize total surplus. Before we delve into the details of the alternative scenarios, we discuss how we address some of the computational challenges associated with the solution of the dynamic model in order to obtain the optimal investment levels.

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.[31]

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

[31]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.

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.

The investment problem is non-stationary because prices, demand, new investment heat rates, and CO_2 targets, change each year. We want to capture the non-stationarity since we are interested in economic outcomes in the medium run. 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.

Given that the state space grows exponentially with the number of firm, 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.[32] We refer to the player that moves first as the leader and the player that moves second as the follower.

Regarding the optimal investment scenarios outside a strategic interaction framework, we compare market outcomes with a single and separate CO_2 markets assuming a single firm chooses investment to maximize industry profit. This is an environment of extreme concentration in investment. We also compare outcomes across the two implementations of the CO_2 markets assuming a single agent chooses investment to maximize the sum of consumer surplus and profit approximating a competitive investment environment as in Bushnell et al. (2017b).

[32]The assumption of sequential move in order to be able to select a unique equilibrium has been used extensively in entry games, where multiple equilibria complicate model predictions. See Bresnahan and Reiss (1990) Berry (1992) for early examples in a static setting, and, more recently, Abbring and Campbell (2010) in an infinite-horizon setting.

6.3.1 Leader-Follower Investment Game

We setup a two-firm investment game by allocating all the plants owned by the strategic firms equally among two firms. Each firm decides strategically on investment taking into account profits earned from the plants it owns and how investment changes endogenous state variables, which include the BAT capacity of both firms. 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.

Our first scenario is one without CO_2 targets (2F-NOCO_2) in which case investment is driven primarily by growth in demand. Given that we allow for an exogenous increase in renewables, the increase in gas-fired BAT capacity we report is in addition to the capacity of renewable sources. As Table 9 shows, aggregate BAT capacity grows to 1,500 MW by 2030 and total welfare is $1,086 billion. Damages from emissions are close to $129 billion.

Our second scenario is without investment in BAT capacity and a single CO_2 market (2F-NOINV). Compared to the scenario without CO_2 targets, total welfare decreases by $10 billion to $1,076 billion. Consumer surplus and damages from emissions also decrease by 10% and 23%, to $922 and and $99 billion, respectively. The decrease in consumer surplus is due to a substantial increase in electricity prices. The increase in electricity prices is driven by the increase in costs because of the CO_2 permit prices and the reshuffling of the industry supply curve. The significant increase in electricity prices is expected because demand is very inelastic.[33] Interestingly, firms benefit from the introduction of CO_2 targets with their profits increasing from $191 to $254 billion.

For our third scenario, we assume a single CO_2 market and optimal investment (2F-SIN). We now see a notable increase in BAT capacity by 2030 to 19,000 MW accounting for approximately 20% of the electricity generation. Relative to the scenario without investment and a single CO_2 market, damages from emissions increase by 11% to $110 billion echoing the concern that exempting new capacity from the CO_2 targets may lead to leakage because of a shift in production from regulated sources to unregulated ones. Nevertheless, total welfare increases by about 5% to $1,130 billion.

The final scenario pertains to optimal investment with separate CO_2 markets (2F-SEP), which leads to an increase in BAT capacity by about 5% to 20,400 MW relative to the

[33]Note that we underestimate the decrease in consumer surplus and the increase in profits because we use impose an upper bound of $50 on the permit prices.

scenario with optimal investment and a single CO_2 market. The increase is sufficient to imply total welfare that exceed its counterpart for the scenario with a single CO_2 market by \$1 billion. Damages from emissions decrease by \$2 billion and, hence, any leakage-related concerns are not warranted.

6.3.2 Industry Profit versus Total Surplus Maximizing Investment

Two scenarios in this section pertain to a single-firm profit-maximizing investment aiming to capture the case of the highest concentration in investment. In the first scenario, we have a single CO_2 market (1F-SIN). In the second scenario, we have separate CO_2 markets (1F-SEP). In the third scenario, a single agent chooses investment to maximize total surplus, that is the sum of consumer surplus and firm profit. This is what we term the competitive investment scenario (COMP) and the resulting equilibrium is equivalent to the solution of the social planner's problem in Bushnell et al. (2017b).

For the scenario with separate CO_2 markets (1F-SEP), BAT capacity in 2030 is essentially at the levels of BAT capacity for the two-firm scenario (2F-SEP). In contrast, BAT capacity in 2030 is only 16,000 MW for the scenario with a single CO_2 market (1F-SIN). Moreover, the evolution of BAT capacity for the single-firm scenarios is much different than the evolution of its counterpart for the two-firm scenarios. Unlike the two-firm scenarios, where we see an immediate increase in BAT capacity at its 2030 level as early as 2013, the growth of the BAT capacity is more gradual and essentially starts in 2022, when the CO_2 targets are introduced, in the single-firm scenario.

Panel (a) of Figure 13 shows the share of BAT capacity in electricity generation for our main optimal-investment scenarios during 2012–2030. In the case of competitive investment, the share of generation from BAT capacity is much higher and begins earlier. By 2015, the BAT share rises to more than 40% reaching 55% by 2030. For the scenario with two firms and separate CO_2 markets (2F-SEP), generation from BAT capacity accounts for about 25% of total generation in 2013 and declines steadily to around 20% by 2030.

Panel (b) of Figure 13 shows the BAT capacity of the leader and the follower for the two alternative scenarios regarding the CO_2 markets. Because of the sequential nature of the investment game between the two firms, the leader immediately invests on the steady state level of BAT capacity to deter investment from the follower. The follower invests zero in BAT capacity in both scenarios. This strategy allows the leader to take the lion's share of industry profits, as can be seen from Panel (c) of Figure 13. If firms can instead coordinate investment, then it will be optimal to delay investment until 2022, and gradually invest afterwards.

Panel (d) of Figure 13 graphs the time series of the wholesale electricity prices. As expected, electricity prices tend to be higher with separate markets than with a single market, although the gap is not that large due to higher investment in the former. Surprisingly, electricity prices are actually *lower* with separate markets in the scenario with a single profit-maximizing firm. In the presence of separate CO_2 markets, the targets for emissions become more stringent making investment more attractive. The stronger incentive to invest under a more stringent regulatory environment compensates for the inherent inefficiency with separate markets.

When maximizing industry profit, total welfare is \$1,116 billion with separate CO2 markets (1F-SEP) and exceeds its counterpart with a single CO_2 market (1F-SIN) by \$10 billion. In fact, both consumer surplus (\$952 billion) and profits (\$266 billion) are also higher in the 1F-SEP scenario compared to the 1F-SIN scenario by \$8 and \$3 billion, respectively. Actually, the 1F-SIN scenario is superior to the 1F-SEP scenario only in terms of damages from emissions and by a small margin—\$101 billion as opposed to \$102 billion.

It may seem surprising that settings with an "inherent" inefficiency–absence of a single market for correcting the externality–yield higher total welfare. The scenarios with separate CO_2 markets yield higher welfare because they are more effective in correcting a second distortion. This second distortion is associated with the incentive to invest. In particular, profit-maximizing *strategic* firms take into account the effect of investment on price. Given that an increase in investment leads to a decrease in price, firms have a strong incentive to withhold investment. The incentive to withhold investment is particularly strong for the single-firm scenarios.

To assess the incentives to withhold investment, we focus on BAT capacity in the competitive-investment scenario (COMP). BAT capacity in 2030 is 56,000 MW and accounts for more than half of all electricity generation. This amount of BAT capacity is more than double all the scenarios with strategic investment, providing evidence of a strong motive to withhold investment. With 56,000 MW of BAT capacity, the CO_2 targets are non-binding even when they are state-specific. Hence, the market outcomes with single and separate CO_2 markets are identical.[34]

Although welfare is highest in the competitive-investment scenario, damages from emissions are also the highest at \$143 billion exceeding their 2F-NOINV counterpart by 50%. They are

[34]Investment in a zero-profit scenario that we also analyzed is even higher compared to our competitive-investment scenario. As a result, outcomes for single and separate markets are again identical since targets are non-binding.

also higher than the 2F-NOCO_2 damages by $14 billion. The large damages from emissions can be traced back to the large expansion of BAT capacity. Since generation associated with BAT capacity is exempt from the CO_2 targets, concerns about emissions leakage have been raised in the discussion of regulating new capacity. The next subsection discusses a particular policy proposed to address emissions leakage and argues that it can lead to unintended consequences.

6.3.3 Emissions Leakage and the Regulation of New Capacity

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.[35]

To understand the implications of policies to address leakage, we simulate a single-firm optimal investment scenario by taking the equilibrium CO_2 prices from the scenario with industry-profit maximizing and a single CO_2 market (1F-SIN), but not exempting emissions from BAT capacity from CO_2 prices. Given that this approach is equivalent to adjusting the CO_2 targets, we use the term NSC to refer to this scenario. Table 9 shows that NSC investment is practically zero, which lowers welfare by a significant amount relative the 1F-SIN 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. 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.

[35]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.

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.

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 a single 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. In a different paper, we relax this assumption and explore the geographic dimension of the firm's investment choices.

Given the recent developments in U.S. environmental policy, at the time we write the paper, 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 incentivize 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.

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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 2.1.

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

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

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

Table 3: Clean Power Plan baseline generation for 2012

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

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

Table 4: List of strategic firms

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

Table 5: Fringe supply

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

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

Table 6: Target policy equation

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

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

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

Fuel	est.	s.e.
gas	1,063,551	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 (MW)	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.

Table 9: Summary of outcomes for alternative investment scenarios

Scenario	2030 BAT Capacity MW	Consumer Surplus $ billion	Firm Profit $ billion	Emissions Damages $ billion	Total Welfare $ billion
2F-NOCO$_2$	1,500	1,023.4	191.4	128.8	1,086.0
2F-NOINV	0	921.7	253.5	99.0	1,076.3
2F-SIN	19,150	1,016.1	224.2	110.0	1,130.4
2F-SEP	20,400	994.4	244.0	107.5	1,130.9
1F-SIN	16,450	944.1	263.3	101.0	1,106.4
1F-SEP	20,350	951.6	266.0	101.5	1,116.1
COMP	56,315	1,183.9	99.2	142.7	1,140.4
NSC	100	925.3	251.3	99.1	1,077.5

Note: BAT refers to best available technology. Total welfare equals consumer surplus 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 values in the 4 rightmost columns 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.

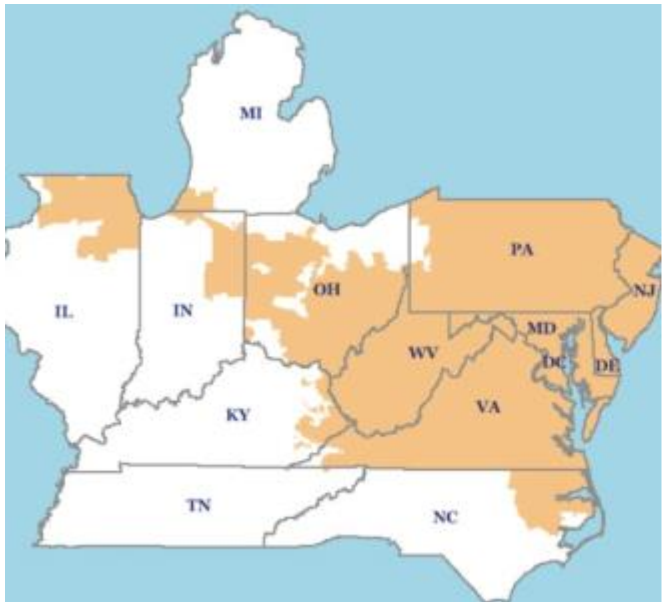
Table 10: Description of alternative investment scenarios

Abbreviation	Description
2F-NOCO$_2$	Two-firm investment game, without CO_2 markets
2F-NOINV	Two-firm investment game, single CO_2 market and no investment
2F-SIN	Two-firm investment game, single CO_2 market
2F-SEP	Two-firm investment game, separate CO_2 markets
1F-SIN	Single-firm investment, a single CO_2 market
1F-SEP	Single-firm investment, a separate CO_2 markets
COMP	Competitive investment, single CO_2 market
NSC	Single-firm investment, single CO_2 market & New Source Complements

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

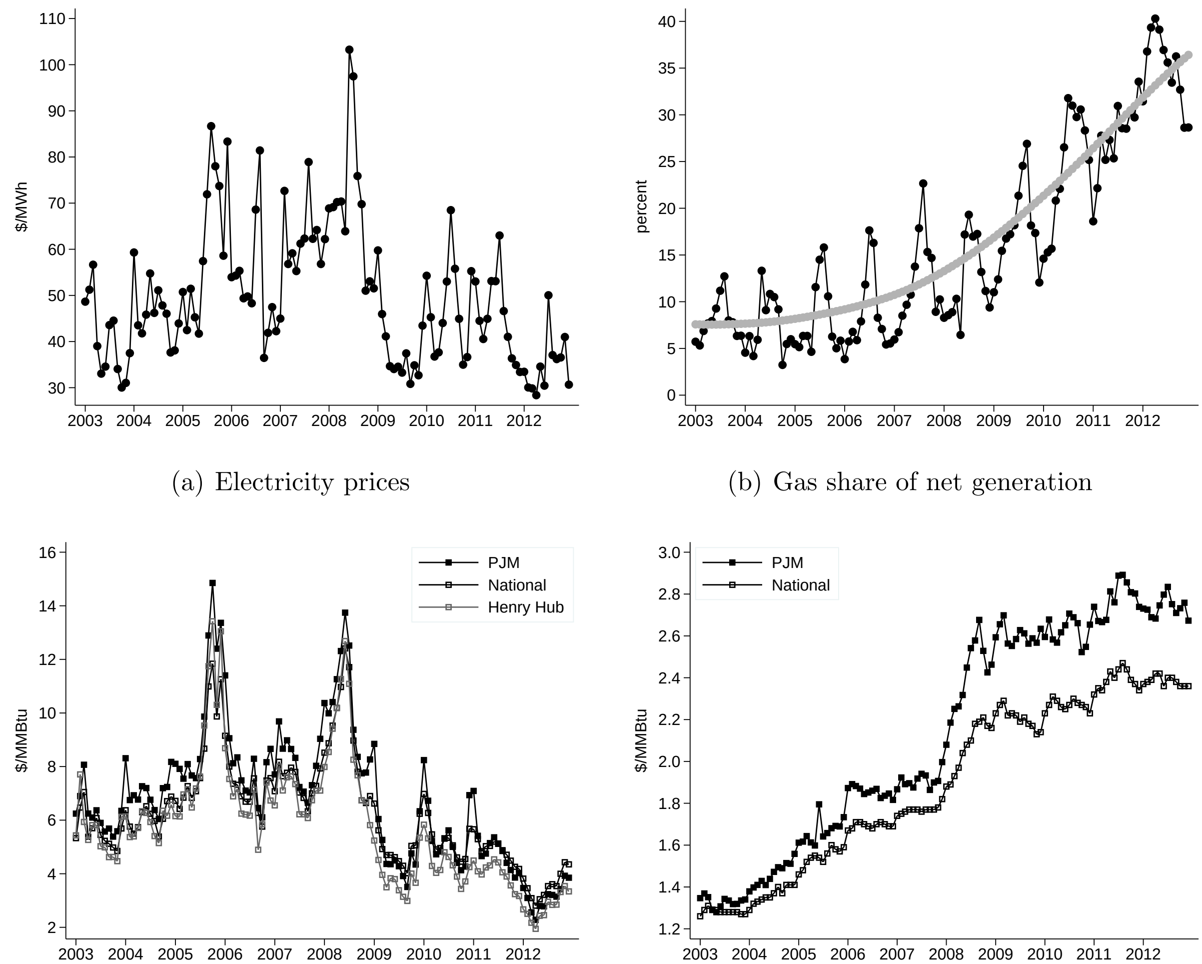
9 Figures

Figure 1: Area covered by the Pennsylvania-Jersey-Maryland (PJM) Interconnection



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

Figure 2: Electricity and fuel prices (2003–2012)



(a) Electricity prices

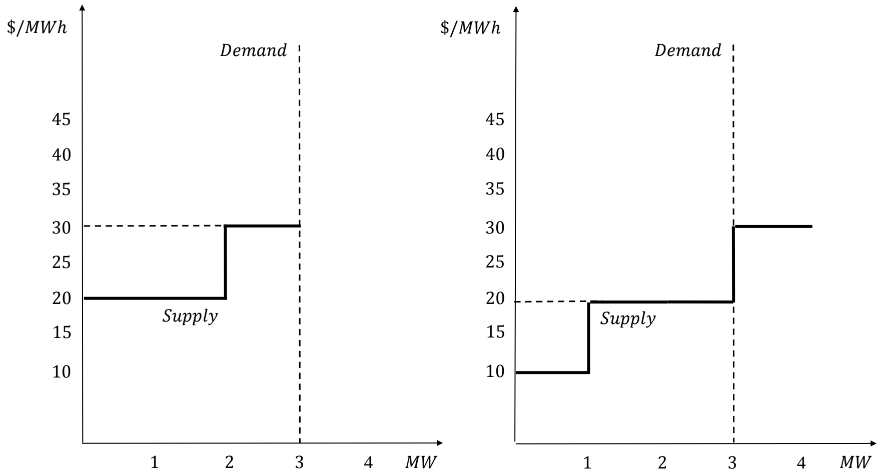
(b) Gas share of net generation

(c) Gas prices

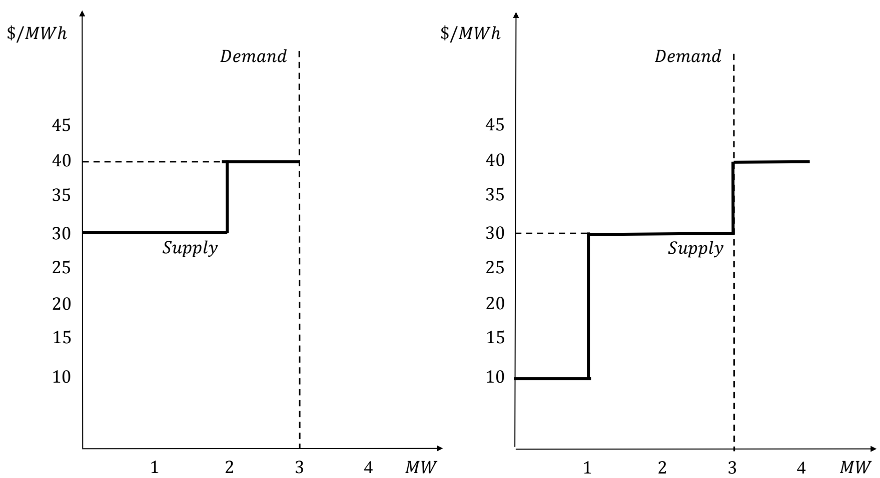
(d) Coal prices

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.

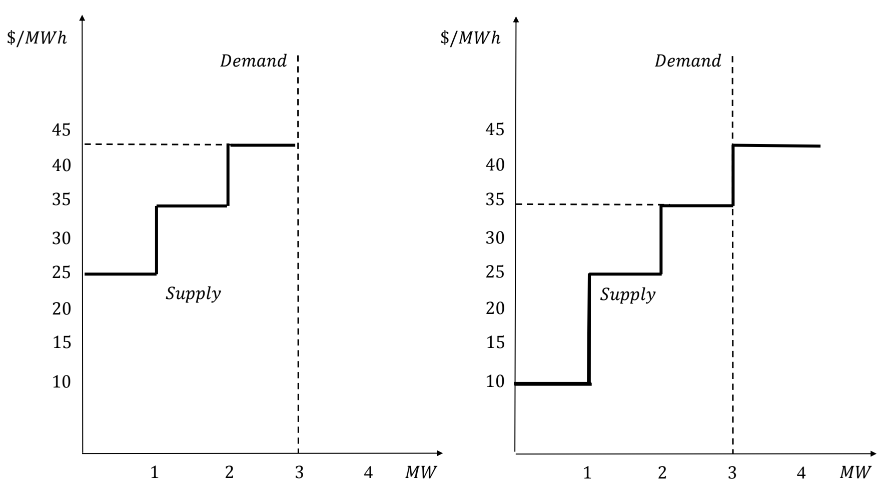
Figure 3: Investment incentives under alternative policy implementation scenarios



(a) No implementation: without investment (left) and with investment (right)



(b) Regional: without investment (left) and with investment (right)



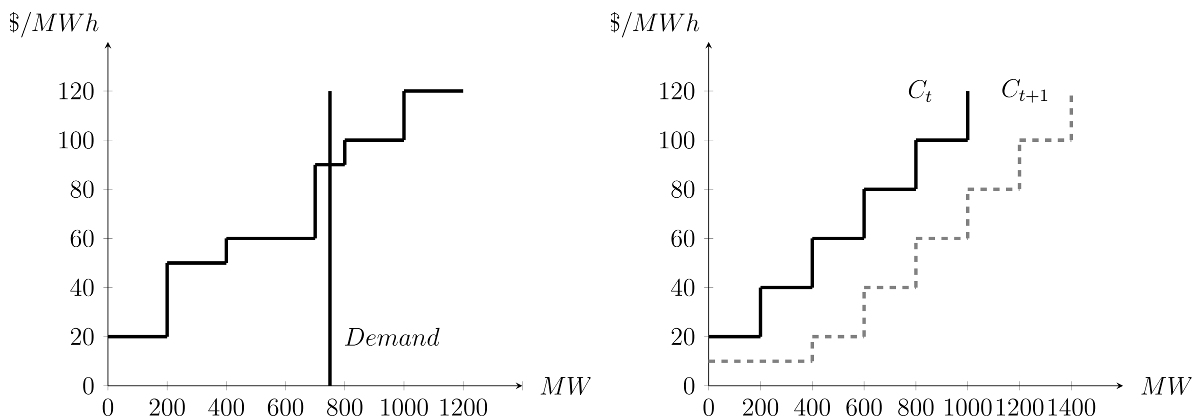
(c) State-by-state: without investment (left) and with investment (right)

Figure 4: Overview of the model timing

2012	$\longrightarrow$	2013	$\longrightarrow$	2014
	Demand parameters	$\downarrow$	Demand parameters	
	$\underbrace{\text{Cost functions}}$		$\underbrace{\textbf{Cost functions}}$	
	Electricity Market	**Investment**	Electricity Market	

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

Figure 5: Merit order and best available technology

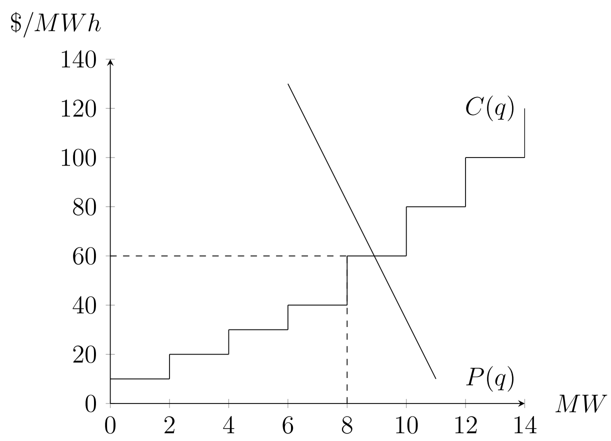


(a) merit order

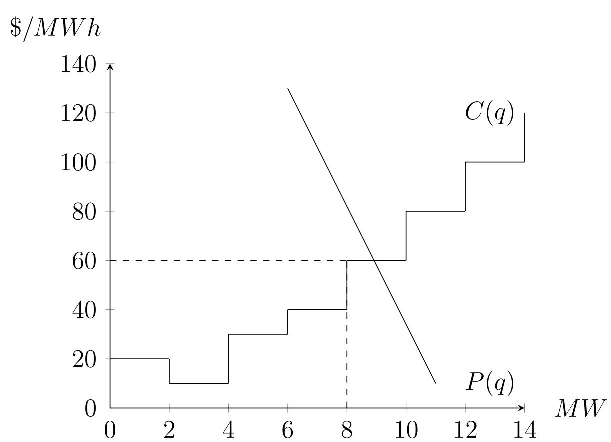
(b) best available technology

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 $t+1$.

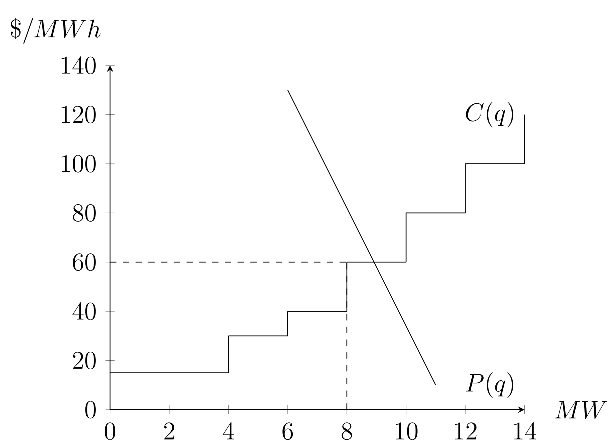
Figure 6: Merit order invariance with inframarginal units



(a) Demand and supply

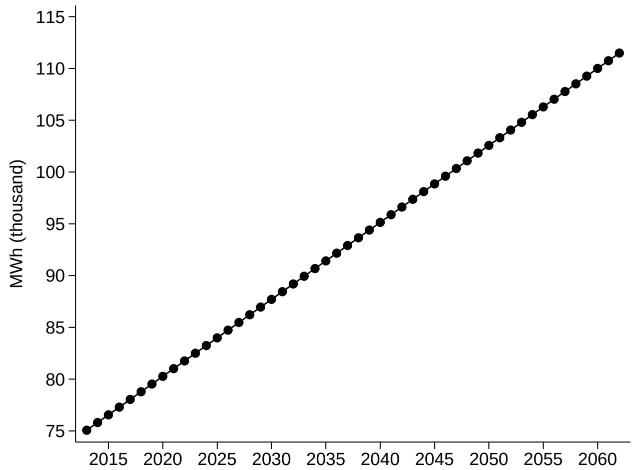


(b) Invariance to rearrangement

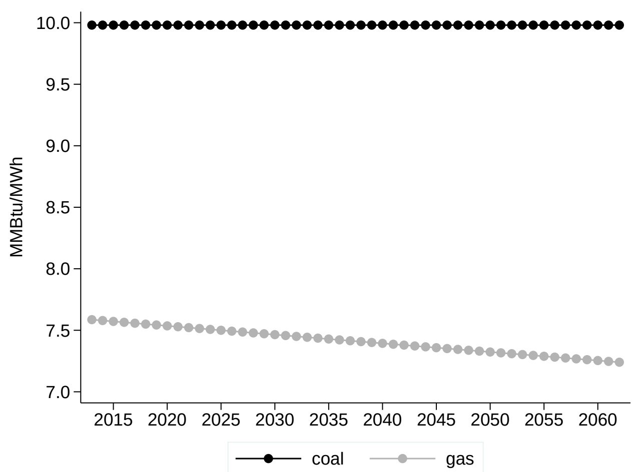


(c) Invariance to averaging

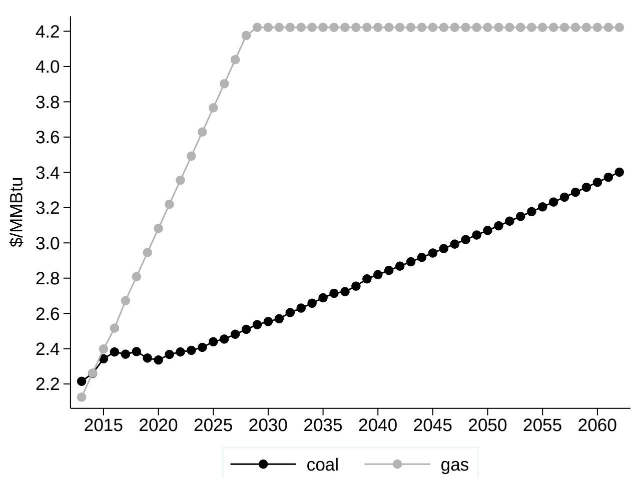
Figure 7: Paths of exogenous variables, 2013–2062



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

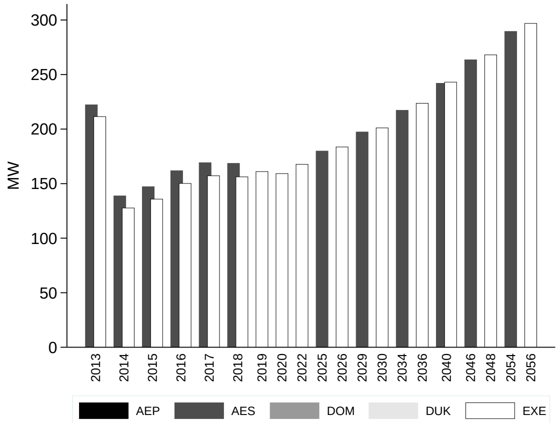


(b) heat rates for new investment

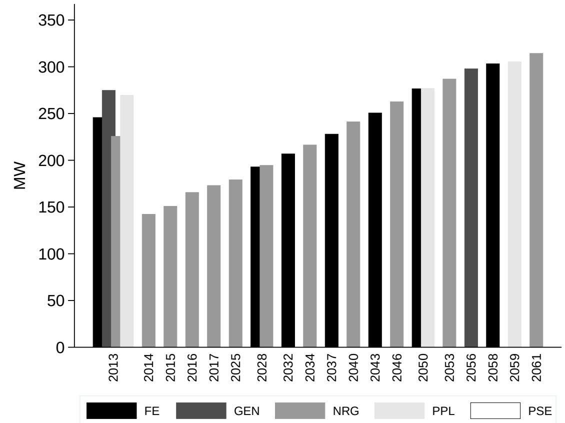


(c) fuel prices

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



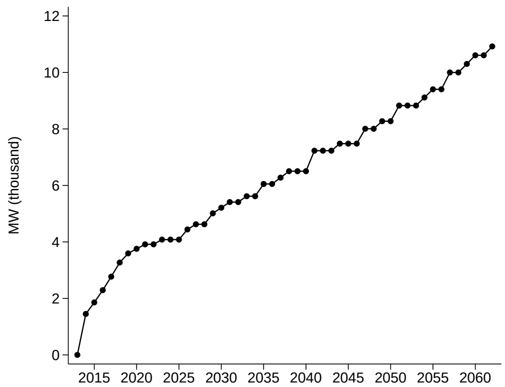
(a) 1st group



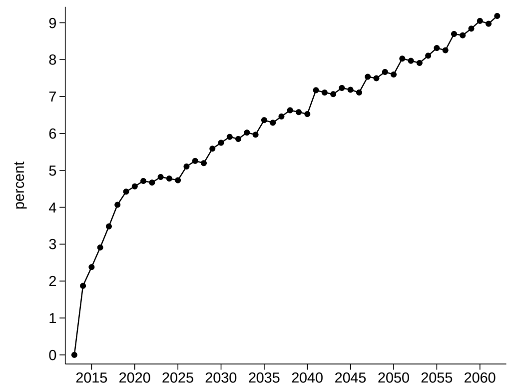
(b) 2nd group

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.

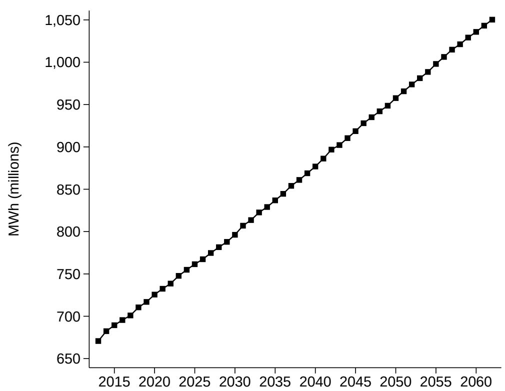
Figure 9: Paths of endogenous variables, 2013–2062



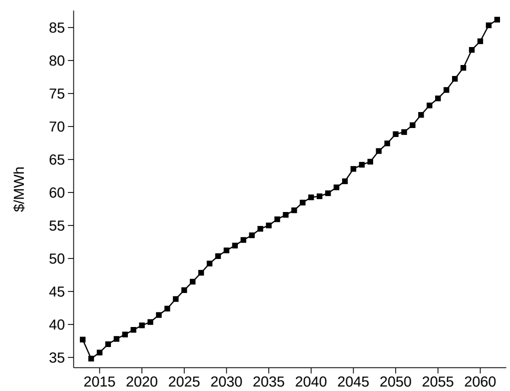
(a) BAT capacity



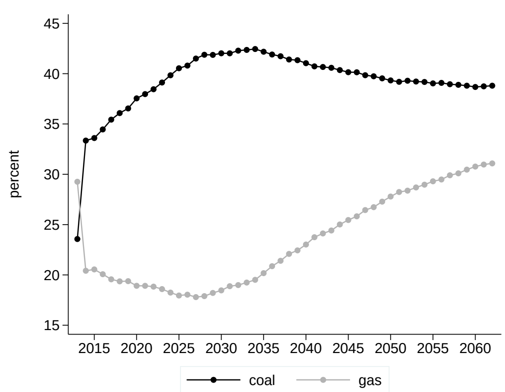
(b) BAT capacity: generation %



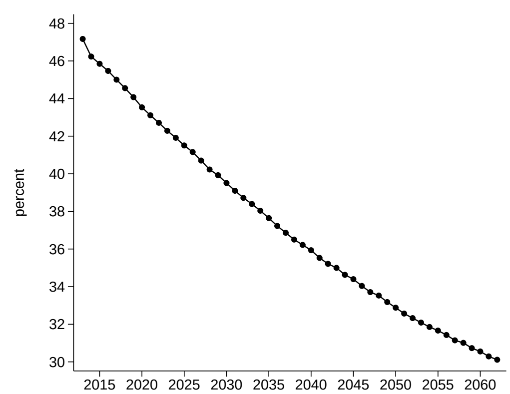
(c) electricity generation



(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

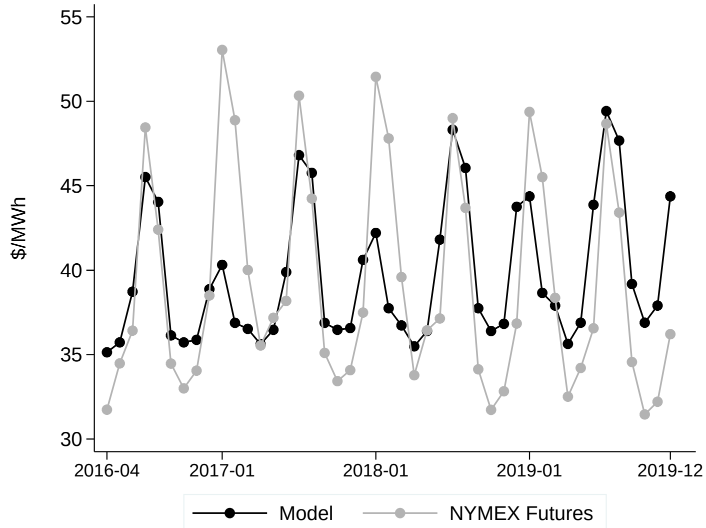
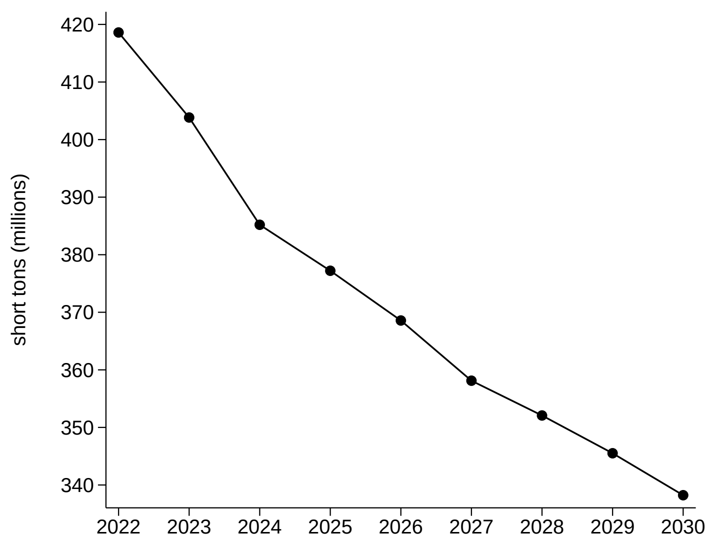
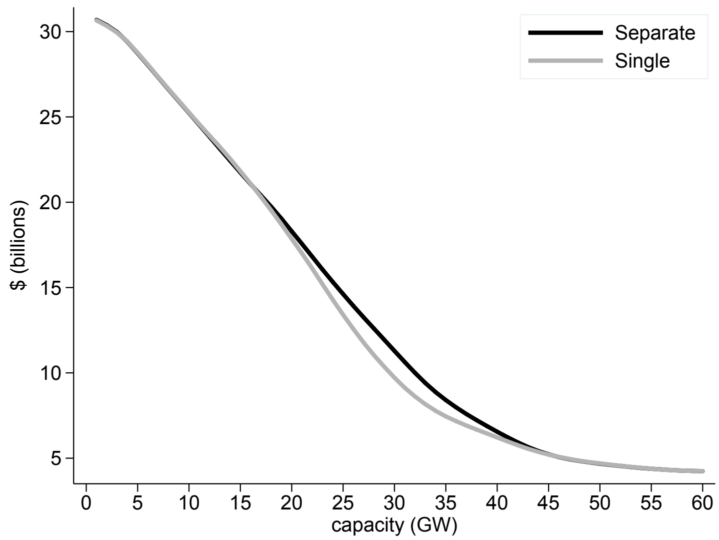


Figure 11: Regional CPP mass-based targets



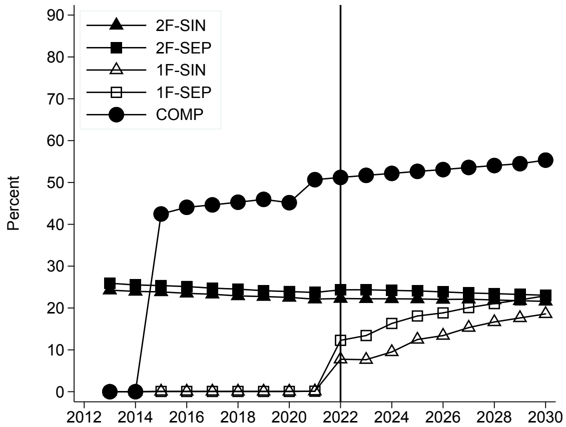
Note: The mass-based target in this figure is based on the supporting data file for CPP compliance from PJM (2016) and are based on electric generating units in the PJM footprint for each state noting that PJM covers only parts of IL, IN, KY, and NC. We plot the sum of state mass-based targets from panel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

Figure 12: Electricity generation cost for the exogenous investment scenario

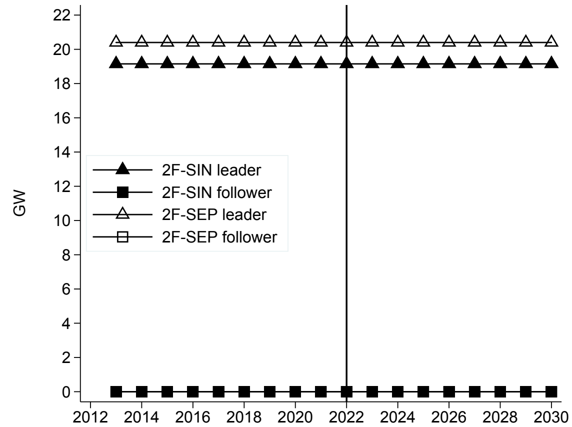


Note: The figure shows electricity generation cost in 2030 as a function of BAT capacity with single and separate CO_2 markets. BAT refers to best available technology.

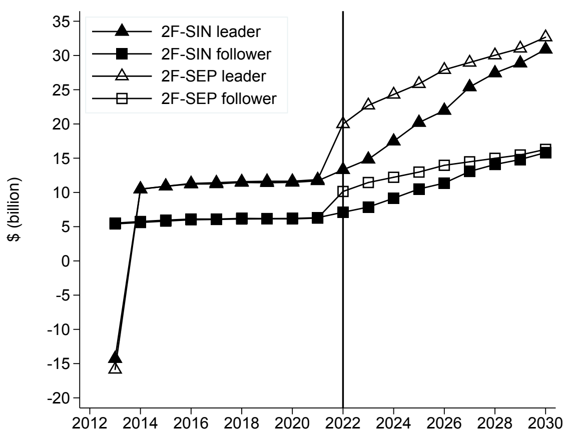
Figure 13: Market outcomes for optimal investment scenarios I



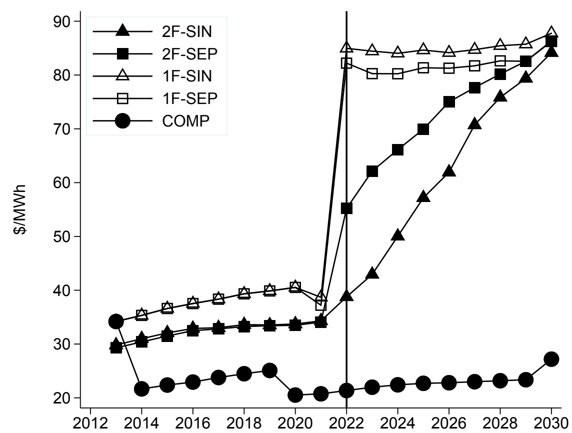
(a) BAT capacity: generation %



(b) BAT capacity



(c) Annual net profits



(d) Electricity price

Note: Table 10 provides a brief description of the alternative investment scenarios discussed in detail in Section 6. BAT refers to best available technology.

A Online Appendix

NOT FOR PUBLICATION

A.1 Data

Our empirical analyses require us to track the expansion of the PJM footprint over time due to zone additions. We identified the additions using publicly available data on estimated hourly load by region in the PJM Markets & Operation website, as well as reviewing the PJM State-of-The-Market (SOM) Reports from Monitoring Analytics; the reports are also publicly available.[36]

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.[37] We identified plants in the PJM footprint using the approach in Knittel et al. (2015).

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.[38] The annual data on plant operating expenses are from SNL.[39]

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.[40] 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.

[36] 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.

[37] 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.

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

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

[40] 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.

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.[41]

The SO_2 and seasonal NO_x permit prices are from Evolution Markets, a permit brokerage firm we identified from the EPA website.[42] The Weather used in the estimation of the fringe supply equations are from the National Oceanic and Atmospheric Administration (NOAA).[43]

A.2 Descriptive Statistics

Tables A1 and A2 provide information regarding the number of plants, generation, and capacity that the strategic firms account for between 2003 and 2012. The number of plants for the strategic firms increased from 47 in 2003 to 109 in 2012. We also see an increase in the number for both coal- and gas-fired units. In the former case, we see an increase from 55 to 135 units. In the latter case, we see an increase from 107 to 262 units. The strategic firms' share of coal-fired (gas-fired) capacity increased (decreased) from 71% (58%) in 2003 to 82.5% (50%) in 2012. We see a similar pattern in the strategic firms' share of coal- and gas-fired generation: an increase from 74% to 88% and a decrease from 61% to 55%.

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.[44] 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.

[41] 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.

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

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

[44] 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.

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 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 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, and AES, dominate gas accounting for 26%, 23%, and 12% of the capacity, on average, during the same 10-year window.

A.3 Endogenous State Variables

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

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

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

AEP is leading coal-fired generation with more than 100 million MWh of coal-fired capacity in every year between 2014 and 2062 reaching 140 million MWh by the end of the 50-year window. Genon, the second largest player in coal-fired generation, experiences a significant increase in coal-fired generation from 16 million MWh in 2013 to 60 million MWh in 2062. We also see an increase in coal-fired generation for Dominion, Duke, and PPL.

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

A.4 Investment Cost 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:

$$\Gamma_{jt} = \gamma_{jt} \times i_{jt}^{ng}, \tag{A1}$$

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:

$$\begin{aligned} E_{\nu_{jt}}\left[\pi_{jt}\right] = \overline{\pi}_{jt} - E_{\nu_{jt}}\left(\gamma_{jt} i_{jt}^{ng}\right) &= \overline{\pi}_{jt} - E_{\nu_{jt}}\left(\gamma_{jt}\right) E_{\nu_{jt}}\left(i_{jt}^{ng}\right) - Cov\left(\gamma_{jt}, i_{jt}^{ng}\right) \\ &= \overline{\pi}_{jt} - \overline{\gamma} E_{\nu_{jt}}\left(i_{jt}^{ng}\right) - Cov\left(\gamma_{jt}, i_{jt}^{ng}\right) \end{aligned} \tag{A2}$$

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:

$$\begin{aligned} E_{\nu_{jt}}\left[\widetilde{\pi}_{jt}\right] &= \overline{\pi}_{jt} - \overline{\gamma} E_{\nu_{jt}}\left(\widetilde{i}_{jt}^{ng}\right) - Cov\left(\gamma_{jt}, \widetilde{i}_{jt}^{ng}\right) \\ &= \overline{\pi}_{jt} - \overline{\gamma}\left(E_{\nu_{jt}}\left(i_{jt}^{ng}\right) + \chi\right) - Cov\left(\gamma_{jt}, i_{jt}^{ng}\right). \end{aligned} \tag{A3}$$

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 (A2) and the value function based on (A3) across perturbations, is not a function of the covariance term as it cancels out once we calculate the difference. Therefore, the additive perturbations allow us to infer the first moment of the heterogeneity in investment costs but not the second.

A.5 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:

$$P_t^C = \min\{P : \sum_{s \in S} \sum_{i \in s} \left(q_{ist}(P) \times HR_{ist} \times r_{ist}\right) \leq \sum_{s} \overline{E}_{st}\}. \tag{A4}$$

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

$$\mathbf{P}_t^C = \min\{\mathbf{P} : \sum_{i \in s} \left(q_{ist}(\mathbf{P}) \times HR_{ist} \times r_{ist}\right) \leq \overline{E}_{st}\} \quad \forall s \in S. \tag{A5}$$

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.

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	17.56	9.26	260.23	34.27	70.82	58.30	73.91	60.86
2004	39.70	17.00	665.24	86.06	73.58	53.93	75.81	66.97
2005	44.68	18.70	770.62	98.06	71.35	49.89	74.32	48.64
2006	44.52	19.22	759.45	105.72	83.32	57.16	87.17	54.88
2007	36.24	19.21	598.49	131.15	86.62	55.72	89.90	64.22
2008	36.20	19.83	561.91	131.69	87.95	57.17	90.70	64.45
2009	37.26	20.71	495.95	163.65	88.27	57.09	91.33	63.43
2010	32.00	22.08	437.03	215.74	83.04	55.74	87.47	60.51
2011	38.07	24.08	459.13	265.00	85.00	49.41	90.75	55.57
2012	40.40	25.87	422.97	344.02	82.50	49.56	87.79	55.17

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 70% of coal capacity and 61% 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.

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

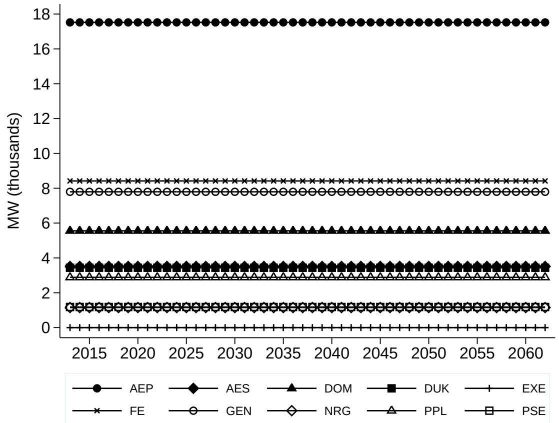
(b) gas

Table A5: PJM Real-Time Energy Market

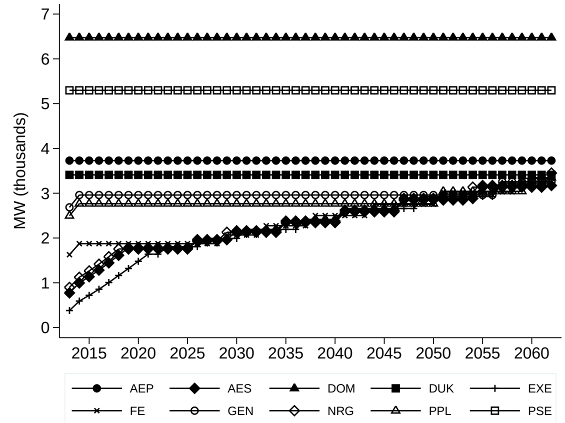
year	price	load	value
2003	$41.23	37,395	$13,506,131,646
2004	$44.34	49,963	$19,406,548,519
2005	$63.46	78,150	$43,444,335,240
2006	$53.35	79,471	$37,140,453,966
2007	$61.66	81,681	$44,119,306,030
2008	$71.13	79,515	$49,545,701,082
2009	$39.05	76,034	$26,009,558,652
2010	$48.35	79,611	$33,718,920,606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

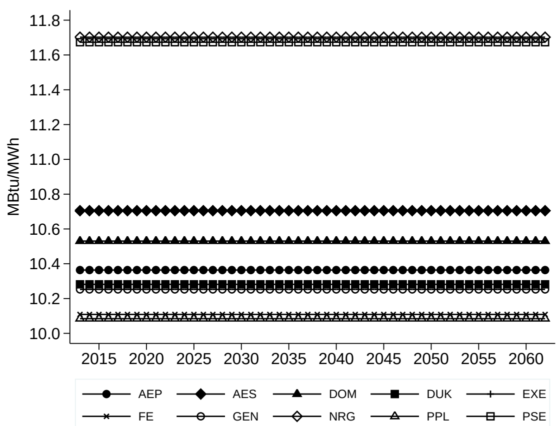
Figure A1: Paths of endogenous variables II, 2013–2062



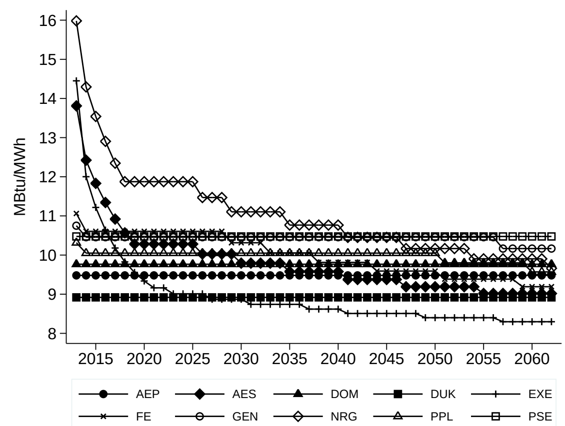
(a) coal capacity



(b) gas capacity



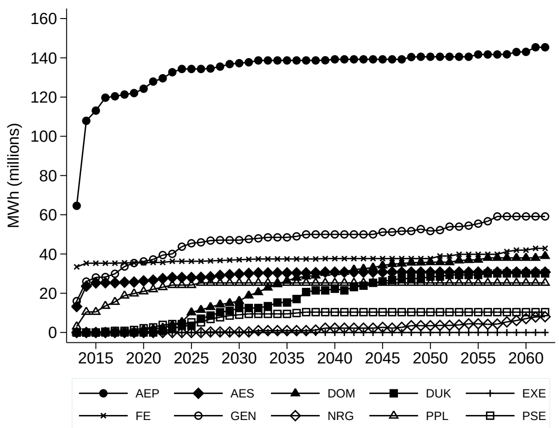
(c) coal heat rate



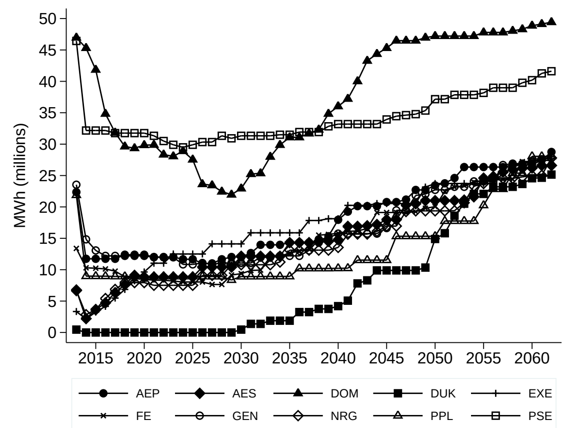
(d) gas heat rate

Note: The heat rates are weighted averages using capacity as weight.

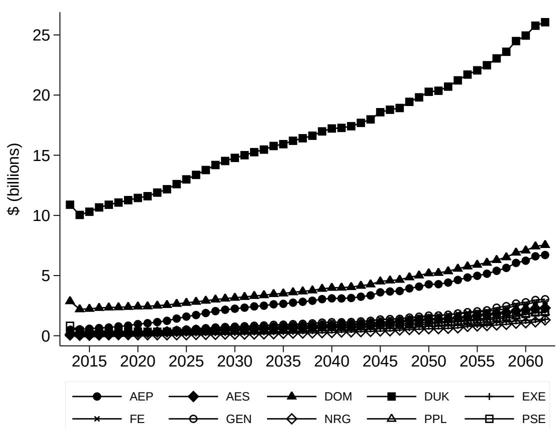
Figure A2: Paths of endogenous variables III, 2013–2062



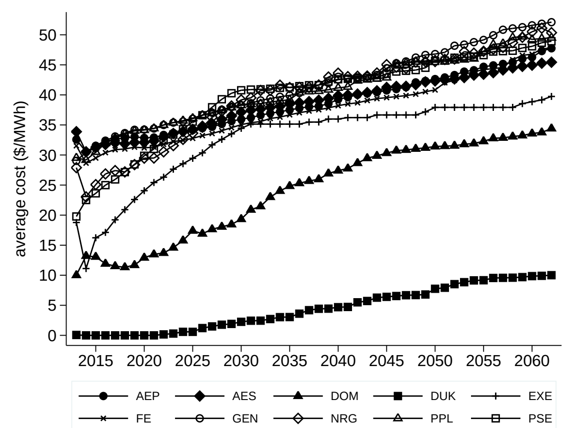
(a) coal generation



(b) gas generation



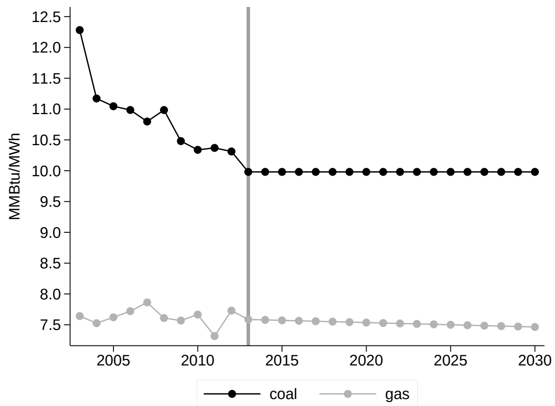
(c) profit from electricity sales



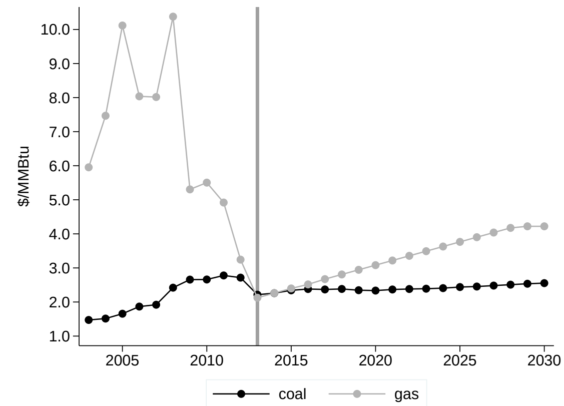
(d) cost of electricity

Note: The profit from electricity sales exclude investment costs.

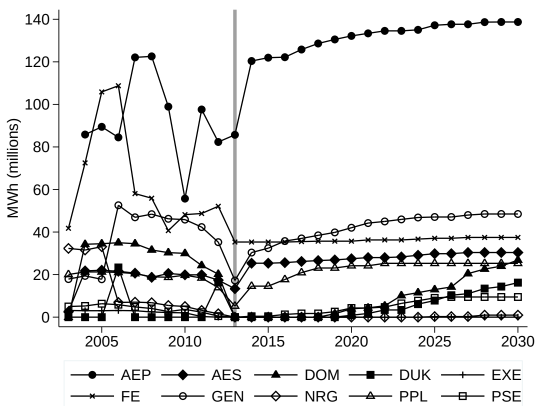
Figure A3: Data and model predictions, 2003–2030



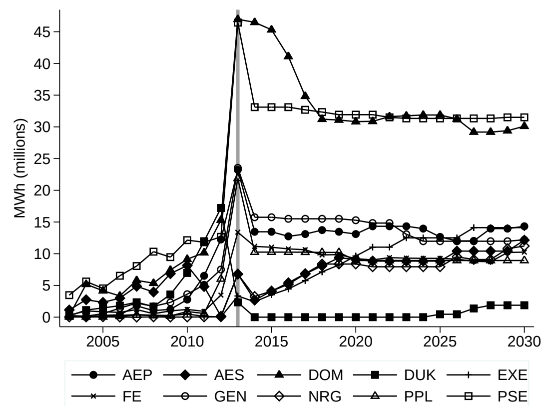
(a) BAT heat rates



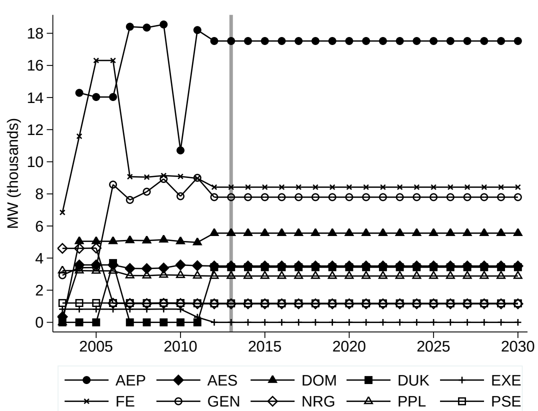
(b) fuel prices



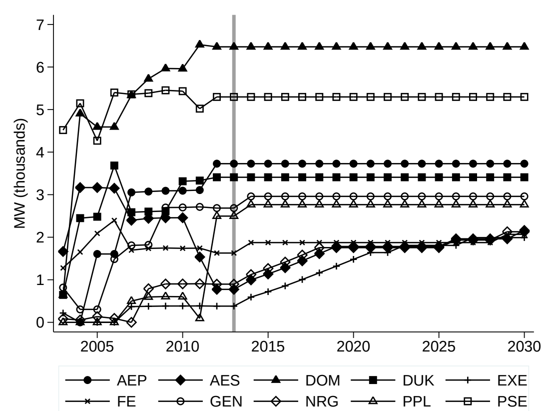
(c) coal generation



(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.

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MIT Center for Energy and Environmental Policy Research
77 Massachusetts Avenue, E19-411
Cambridge, MA 02139
USA

Website: ceepr.mit.edu

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