The Effect of Capacity Payments on Peaking Generator Availability in PJM

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Abstract

This paper aims to study the effects of capacity payments on the operational decisions of plant managers for peaking units in the PJM Interconnection. We achieve this through a structural estimation of maintenance and switching costs between the operational state, the standby state and retirement of generating units. We have focused on the period from 2001 throughout 2016—a period where we have identified some significant changes in the power market dynamics. We conduct a counterfactual analysis on the level of capacity payments to study the effects of introducing a capacity market in 2007. The reliability of the power system depends crucially on the availability of flexible peaking units to cover load in periods of high demand. Therefore, an understanding of the real costs facing the owners of these units is essential in order to enforce policies that ensure sufficient peak capacity in the power system. Our study aims to analyze the effects of this additional market on switching behavior.

The empirical data shows less switching between states after the introduction of capacity remunerations. We find that the role of peaking units has changed, with the units being dispatched more often. In the counterfactual analysis, we find a clear connection between the level of capacity payments and switching. We conclude that the current level of capacity payments in PJM incentivizes peaking units to stay in the operational state.

Introduction

With increasing amounts of uncontrollable generation from intermittent energy sources such as solar and wind, the uncertainty regarding the reliability of supply increases, and generating units that can be ramped up on short notice will be even more crucial. In many electricity markets, regulators have concluded that capacity remuneration mechanisms are needed to ensure adequacy and reliability. In a capacity market, in addition to payment for delivered energy, the generators receive a fixed remuneration for the capacity that they can offer into the power system, regardless of whether or not they are dispatched in the energy auction.

The PJM capacity remuneration mechanism, the Reliability Pricing Model (RPM), was launched in 2007 to address growing issues regarding the fulfillment of capacity obligations in the market. PJM holds annual capacity auctions three years in advance, where generators commit to one year of capacity delivery.

We observe a different pattern of switching activity after the introduction of the RPM and employ a structural model to quantify these changes. We also consider current US power markets trends, where the natural gas price has dropped and units previously serving solely as peak generators are now serving loads more often. Besides, a series of new environmental regulations has been introduced. Finally, we explore the effect of different levels of capacity remuneration in a counterfactual analysis.

In the literature, a variety of different models have been used to study the effect of capacity markets on investments in capacity. Hach et al. (2016) use an iterative dynamic capacity model to study investments in capacity. Petitet et al. (2017) and Cepeda and Finon (2013) utilize a similar long-term system dynamics model incorporating new investments in large-scale RES projects to assess the capacity remuneration mechanism. Bhagwat et al. (2017) use a bottom-up agent-based modeling approach to study the development of electricity markets under imperfect information and uncertainty and assess different capacity remuneration mechanisms. Others, such as Botterud et al. (2002) and Dahlan and Kirschen (2014) use dynamic simulation optimization to model the capacity investments in deregulated power markets. Fleten et al. (2017) analyze the effect of the newly introduced US capacity markets using structural estimation in an empirical study of peaking unit switching costs, but lacked data on the capacity payments.

The estimation of parameters in structural models and dynamic games of entry and exit is an active sub-area within empirical industrial organization. Computation time has been a major issue since the seminal work of Rust (1987) was published, introducing the Nested Fixed Point Algorithm (NFXP) for estimating the optimal stopping problem of bus-engine replacements in a discrete choice model. It relies on finding the set of predictions that most closely represent the data for each guess of a set of structural model parameters—a computationally overwhelming task even by today's standards. Since then, alternative approaches has been proposed; see Pakes et al. (2007), Aguirregabiria and Mira (2007), Bajari et al. (2007), Pesendorfer, and Schmidt-Dengler (2008) for methods of estimating dynamic games. These papers build on the two-step approach introduced by Hotz and Miller (1993) for estimating single agent dynamic discrete choice models using the Conditional Choice Probability estimator.

However, Su and Judd (2012) conclude that many of these methods are not asymptotically efficient, and introduce a constrained optimization approach, where the maximum likelihood of observing the data is found subject to constraints that ensure optimality of the solution. This significantly reduces computational time compared to the NFXP algorithm, since the constraints do not need to be satisfied until the last iteration of the algorithm. Our work builds on this branch of the structural estimation literature, through slightly revised versions of the model formulations in Fleten et al. (2016, 2017).

Relevant applications of structural models include Thome and Lin Lawell (2015). They employ both a reduced-form discrete response model and a structural model of a dynamic game, building on the model developed by Pakes et al. (2007), to model the decision to invest in corn-based ethanol plants in the Midwestern United States. They find that there is a significant strategic component present when making investment decisions in corn-ethanol plants. Aguirregabiria et al. (2007) use an extended version of the Nested Pseudo Likelihood estimation method from Aguirregabiria and Mira (2007) when developing a dynamic model of entry, exit, and growth in the oligopolistic Chilean retail market. Fleten et al. (2016) address the strategic component of competition between players in the North-Eastern American electricity markets through an element in the state variable vector capturing the competitive advantage between different generators within the same US state. We further refine this approach by calculating the relative competitive advantage within the generators' transmission zone, a more relevant measure of competitiveness.

We contribute to the literature by developing a structural model to estimate the switching costs of peaking generators in the PJM Interconnection with capacity payments and account for other major exogenous factors. Structural estimation of cost structures in power markets with capacity payments is as far as we know new to the literature. Further, the use of zonal resolution for electricity and capacity prices as well as for the measure of competitiveness makes us able to implicitly include information on congestion in the power system, something that earlier structural estimations of power system costs have not considered.

Methods

In order to design a market where peak generators are compensated appropriately to secure sufficient investment activity, a regulator must have a thorough understanding of the generators' cost structure as well as the market dynamics. Regulators make cost estimates, but empirical testing of such estimates is difficult. Generator costs are influenced by exogenous factors that can be hard to observe. In addition, the cost structure of a power producer is business sensitive information, as this determines the lower limit of their bids in market auctions. Therefore, the empirical estimation of generator costs is one of few viable options for investigating the real costs faced by generators. The business decisions of an owner of a peaking unit are readily formulated as a sequential decision process in time, where choices about the operational state of the generator must be made before each consecutive time period. Markov decision processes provide an excellent framework for modeling sequential decision making under uncertainty (Rust, 1994). Under the assumption that the generator owners act rationally, dynamic programming provides a way of identifying the optimal decision rule for choosing how to operate one's generator. The agent can be represented through a set of economic primitives, describing their utility function, transition probabilities and discount factor for future states. The primitives convey information about the decision process of the generator owner as well as the uncertainty of the decision environment. Structural estimation provides a framework for robustly estimating such primitives.

Background and Data

We analyze data on PJM peaking generators from 2001 until 2016, extending the time frame of Fleten et al. (2016, 2017), who used data on peaking units from the PJM Interconnection, as well as ISO-NE and NYISO. We have data on a total of 859 unique generators from 252 different power plants, giving us a total of 10401 generator-year observations.

Our main sources of data are the Energy Information Administration (EIA), the U.S. Environmental Protection Agency (EPA) and PJM. Form EIA-860 provide generator-level specific data about existing power plants with 1 MW or greater of combined nameplate capacity. This form also reports on the current status of the individual generator, which can be in one of three possible states; Operational (OP), Stand-by (SB) or Retired (RE). In OP state, the power plant can start production on short notice. In SB state, the plant is temporarily shut down to reduce maintenance costs, and cannot be used in power production before it is switched back to OP state. A plant in RE state is considered abandoned, and cannot be used for power production in the future.

Under the Reliability Pricing Model (RPM), PJM holds annual capacity auctions three years in advance, where generators commit to one year of capacity delivery. The bids of the generators add up to the capacity supply curve. To stay competitive, it is vital for the peaking units to clear the capacity auctions to cover their fixed costs. Therefore, it is reasonable to assume that all generators will bid in their maximum allowed[1] capacity in the capacity auctions. One fundamental characteristic of the RPM is that constraints in the transmission and distribution grids are recognized, and zonal capacity prices are used to incentivize the right level of capacity delivery for each zone.

Since the implementation of the RPM and up to the 2015/16 delivery year, a total of 28400 MW of capacity has been added in the PJM Interconnection. Table 1 shows the distribution of sources of new capacity. Our analysis will only take new generation and plant reactivation into account, amounting to approximately 20% of the total increase in generation capacity. The low share of plant reactivation indicates that there exists a cost of reactivating a power plant that is higher than the cost of demand response[2], which amounts for most of the added capacity after the introduction of RPM.

Table 1: Sources of new capacity under RPM (Pfeifenberger et al., 2011)

Source	*MW*	%
Demand response	11 800	41.5
Net change in exports/imports	6 900	24.3
New generation	4 800	16.9
Plant uprates	4 100	14.4
Plant reactivation	800	2.8

In addition to the introduction of a capacity market, several other exogenous factors have changed in the PJM in recent years. The United States Environmental Protection Agency (EPA) is responsible for environmental regulation standards. Examples are the NOx budget trading program (NBP), the Clean Air Interstate Rule (CAIR) and the Cross-State Air Pollution Rule (CSAPR), all introduced between 2003 and 2014. These regulations are cap and trade programs, designed to reduce the environmental impact from power plants and industrial units, primarily emissions of nitrogen oxides (NOx) and sulfur dioxide (SO2). A generator can become compliant through technology upgrades or by trading in the markets established by the EPA. These programs all affect generators operating in PJM, and thus their effects should be controlled for in an analysis of switching costs in this area.

[1] Generators are not allowed to bid in their nameplate capacity, as generator outages must be accounted for.
[2] Demand response is the mechanism where consumers are financially compensated for reducing load in peak hours.

Another macroeconomic factor that affects the operational decision making for peak generator managers is the emergence of shale gas extraction in the US, which started around 2007. Advances in hydraulic fracturing technology lowered the production costs of shale gas, and by 2016, shale gas amounted for 51%[3] of the total US gas production. Consequently, the price of natural gas dropped significantly after 2008, and has stayed low since. Together with an increased amount of intermittent renewable energy sources (RES) in the baseload, the low price of natural gas acted as a disruptive force in the power generation market, altering the role of the peak generators. Prior to these changes, coal-fired units served as baseload, and combustion turbines were dispatched in periods of peak demand. Today, this picture is somewhat more complex. The intermittent nature of baseload RES requires peaking units to run not only in the short periods of peak demand but also at times where RES are not able to deliver. This effect is amplified by the low variable costs of production following the price drop of natural gas in 2008, making gas turbines rank lower in the merit order of dispatch. Besides, stricter environmental regulations have made older coal-fired units less competitive unless they undergo substantial upgrades. Thus, the competitive landscape has changed for peaking units; they now compete with other peaking units, combined-cycle gas turbines and in the extreme case, conventional baseload plants (Ott, 2012). This might give rise to challenges since peaking units are designed to run at their specified design point for shorter periods of time. We expect these altered patterns of operation for peaking units to affect the maintenance and switching cost estimates.

Next, we consider heat rates. Form EIA-923 gives detailed information about power generation and fuel consumption. From this data, we can calculate the yearly average heat rates for each generator. The heat rate of a generator is defined as the thermal energy input required per unit of electric energy output, measured in MMBtu/kWh. By calculating a yearly reported value, as opposed to using nominal heat rate, we capture the effect of generators running at non-optimal loads for some time during the year. This also enables us to capture the effect of aging equipment and declining efficiency over time. We have form EIA-923 heat rate data on 2952 of the generator-year observations from 273 different generators, which amounts to 28.7% of all observations, and heat rate data being available for at least one year in the period for 31.8% of the generators. For generators where no heat rate data is available, we estimate heat rates using an OLS regression with age and installed capacity as explanatory variables.

Further, the generators face other variable non-fuel operating and maintenance costs (VOM). Following the method from Fleten et al. (2017), we estimate these costs based on the information available in the Annual Energy Outlook document and the accompanying assumptions document (U.S. Energy Information Administration, 2018), where EIA estimates and breaks down the costs of new power plants. As EIA only recently has started publishing these reports, and we have generators in our dataset dating back to the 1960's, data on VOM is not complete. Therefore, we estimate the VOM for each fuel type, by assuming that it is linearly increasing with age.

The time series for historic peak hour (07-22) electricity and capacity prices are collected from PJM's database. There are significant transmission constraints within the transmission and distribution grids in the PJM Interconnection, especially in areas where PJM connects with neighboring RTOs (United States Department of Energy, 2014). PJM uses zonal pricing to address congestion in the power system. The zonal price data published by PJM shows great variations in prices for the different zones, which will affect the profitability of the generators. For this reason, we have matched generators to zones and use zonal prices for electricity and capacity. Capacity payments are yearly fixed payments for committed capacity measured in $/MW-day. We collect historic spot prices of Henry Hub Natural Gas (NG), New York Harbor No. 2 Heating Oil (DFO) and US Gulf Coast Kerosene-Type Jet Fuel (KER), from the EIA.

Similar to Fleten et al. (2017), we calculate a spark spread profitability measure for each generator-year observation based on profits from the sale of electricity, fuel costs and VOM. Our approach deviates from their work in how we use zonal pricing for the PJM Interconnection, thus avoiding the simplification of using the system price for all generators when calculating the spark spread. By mapping generators to price zones, we implicitly account for congestion in the power system.

Data on the individual generator's bids in the capacity auctions is unavailable. However, given that the capacity remuneration mechanisms are designed to cover the fixed costs of generating units, it is reasonable to assume that all peaking units will bid their maximum allowed capacity. By the same reasoning, we also assume that all generators in the operating state clear the capacity auction and receive payments for their full capacity. Peaking units will have no incentive to bid below their allowed capacity, and they are likely rather to enter the standby state than operate if they do not clear the capacity auction to avoid incurring production costs. Therefore, we incorporate the capacity payments in the profitability measure in the period after 2007 by adding the zonal capacity prices. By doing this, we get two different profitability measures: the energy-only profitability measure, which can be calculated for the whole period, and the RPM adjusted profitability measure, which only exists from data from 2007-2016.

[3] Numbers from the US Energy Information Administration.

Table 2 summarizes the data regarding observed switches and profitability.

Table 2: Average yearly payments from energy and capacity markets for all switching decisions. Profitabilities in [$/kW-year].

	Current state	***OP***		***SB***		
	Switching to	***OP***	***SB***	***OP***	***SB***	***RE***
2001-2007	Number of observations	3479	64	161	755	76
	Share	98.2 %	1.8 %	16.2 %	76.1 %	7.7 %
	Average profitability	12.28	5.85	14.25	13.00	5.58
2008-2016	Number of observations	4435	4	15	521	32
	Share	99.9 %	0.1 %	2.6 %	91.7 %	5.6 %
	Energy-only profitability	18.50	11.64	15.67	7.88	9.25
	Capacity payments	40.22	58.59	29.17	45.10	50.91
	Average profitability	58.72	70.23	44.84	52.98	60.15

For the first period, we see that operational generators choose to stay operational in periods of high profitability, shut down in years when the profitability is low, and switch back to OP when profitability picks up. Many generators choose to stay in SB, even with rather high profitability, until they reach a certain threshold, where they switch back into operation. They only choose to retire when profitability drops very low. This behavior aligns well with the re-entry and exit barriers described in real options theory (Dixit and Pindyck, 1994).

After the introduction of the RPM, there are two sources of revenue for generators. The compensation of a generator comprises an element for the electricity produced in real time, varying throughout the day, and a yearly fixed element for the available capacity. This change in the dynamics of the remuneration of generators in RPM complicates the effort of discovering what drives the observed switching behavior. Compared to the period prior to the introduction of the RPM, the number of observed switches is drastically reduced, with only four observations of plants entering SB state and 15 switching back to the OP state. Because of few observations, average profitabilities for these switches should be interpreted with care. However, looking only at the profitability indicator for the energy-only market in Table 2.1, the average profitabilities makes sense when interpreted in a real options perspective. It is worth noting that the average profitability for retiring plants is higher than that of plants entering SB state, but once again, only a few observations with high profitability will have a significant impact on the average. From Table 2, there is no apparent relationship between the capacity payments and the observed switching behavior.

In view of real options literature, the switch from the operational state directly to retirement can be regarded as irrational. One would rather switch to the mothballed (SB) state, recognizing the value of the option to re-enter the market if profitability rises. Therefore, we argue that the few empirically observed switches from OP to RE can be explained by other circumstances. Examples are physical breakdowns of generators due to uncontrollable factors such as natural disasters or retirements caused by state-level regulations. Consequently, we have excluded these observations from our data.

Figure 1 illustrates the observed switching behavior in combination with the distribution of the energy-only spark spread profitability measure for the whole period from 2001 to 2016. The grey shapes illustrate the distribution of profitability, with wider regions indicating more observations for this level of profitability the specific year. The colored lines in the plot describe the observed switching behavior, gathered from Form EIA-860. The figure clearly illustrates that the switching pattern changed after 2007. The development of switches between the operating state and the standby state is most interesting. In the period before 2007, the observed switches seem to develop in accordance with the profitability indicator. In an environment driven mainly by revenue from delivering energy into the power system, one would expect that switching behavior be strongly related to the development in the profitability indicator. In relative terms, there are more switches from the standby state to operating state (SB-OP) when the profitability indicator is high than when it is low. By the same token, we observe few switches from the operating state to the standby state (OP-SB) when profitability is high and many when it is lower. This pattern is not as evident after 2007, with fewer switches between the operational and standby state. It is also worth commenting on the spikes in the retirements in 2003 and the period 2011-2014.

These must be seen in relation to the changes in environmental regulation, because it would be financially irrational to upgrade an old, dirty peaking generator to comply with regulatory requirements. This kind of exogenous factor must be modeled explicitly in the structural estimation, as such information is not available through the development of the profitability indicator.

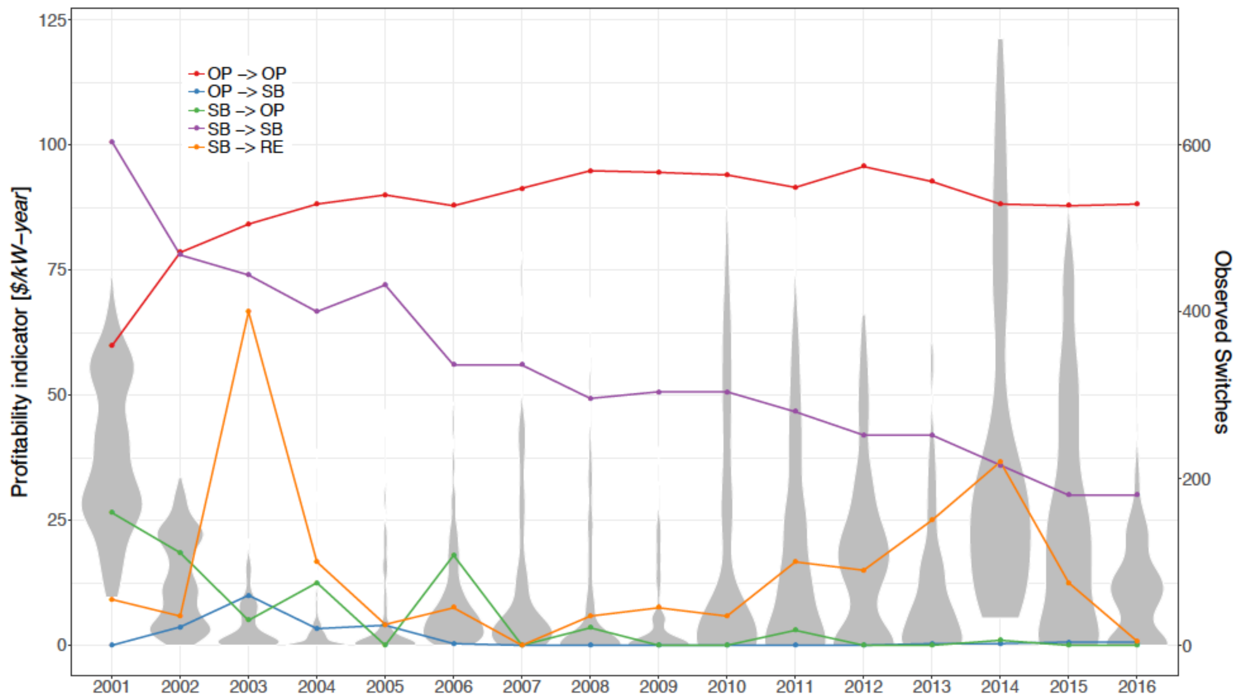


Figure 1. Observed switching behavior and distribution of the energy-only profitability indicator.

It is also worth commenting on the spikes in the retirements in 2003 and the period 2011-2014. These must be seen in relation to the changes in environmental regulation, as discussed in Chapter 1, because it would be financially irrational to upgrade an old, dirty peaking generator to comply with regulatory requirements. This kind of exogenous factor must be modeled explicitly in the structural estimation, as such information is not available through the development of the profitability indicator.

Finally, we specifically consider retirement decisions. PJM state that there are two main drivers of the retirements (PJM Interconnection, L.L.C, 2018). Firstly, the emergence of low-cost shale gas from 2007 onwards led to more competition from new market entrants. Modern and efficient generators have put older units under pressure. The introduction of the RPM coincides with the price drop of natural gas, leading to a drastic change in market conditions. Under RPM, the generators are forced to compete directly on fixed costs, as generators bid in the capacity auction based on their fixed costs. This favors efficiently managed generators. Less efficiently run units can be forced to forfeit the capacity remuneration in cases where they do not clear the capacity auction, possibly forcing the units into retirement.

The second driver mentioned by the PJM concerns the environmental regulations that have been introduced during the period of study. The spike of retirements seen in 2003 must be considered in relation to the introduction of the NOx Budget Trading Program (NBP) in this year. A NOx emission scheme will punish older units more than newer ones, as designs have been improved to reduce emissions (Lefebvre and Ballal, 2010). In addition, there are more retirements seen in the period after 2011. In this period, CAIR was active and later replaced by the CSAPR. Limitations on SO2 emissions and trace elements such as heavy metals will generally hit generators fueled by heavier oil derivates harder than gas-fired units, as the concentration of pollutants is higher in such fuels (Lefebvre and Ballal, 2010). Based on this, it is likely that the stricter environmental regulations will have had an impact on the switching decisions of the generators, and especially on retirements, as owners of older units will face the choice of upgrading a less competitive unit or retire it. As these regulations apply to all generators in the market, some coal-fired baseload plants will be forced into retirement, leading to more frequent dispatching of gas-fired peaking units.

The two main drivers of retirements mentioned by PJM align well with what we observe in our dataset; most retiring capacity is from old plants in both periods. However, the plants that retire after 2007 are on average older. These older plants are in general more polluting and have been hit harder by stricter environmental regulations, in particular, the CAIR and CSAPR. They are not competitive under new regulation and are thus forced into retirement.

We see the same effect in our data, with a very high proportion of retiring capacity running on DFO and KER5, which are dirtier fuels than NG. These observations point us in the direction that the retirements seen after 2007 can be explained by it becoming less favorable to operate older, dirtier plants. It also reflects the first main driver of retirements mentioned by the PJM, that lower NG prices has made these plants more competitive than the DFO- and KER-fired plants.

We also see that there are almost no retirements of capacity from newer units in the latter period, indicating that RPM has been successful in retaining capacity provided by efficient generators. Previous literature, such as (Fleten et al., 2017, 2016) has not recognized this connection between retirements and environmental policy changes.

Analysis

The power market has changed profoundly during the period of observation. The introduction of capacity remunerations, stricter environmental regulations, and the plummeting of natural gas prices contribute to a different market dynamic. For this reason, we are using two model formulations to capture the agent's decision problem in a period where the market situation changes a great deal. First, we employ an energy-only formulation, only considering a generator's spark spread in the energy-only market. In the second model formulation, we include additional factors, which are thought to explain generator switching behavior. Capacity remuneration has also been included in the spark spread calculation after 2007. The energy-only formulation estimates the costs of operating a combustion turbine in a relatively simple market. The capacity market formulation incorporates more variables, resulting in a more complex model that explores the effects of added exogenous variables on the agent's decision problem. The added complexity will reduce the relevance of the estimates as a means of unveiling actual costs but will give insight into how the external factors affect the agent's decision problem.

Here, i denotes a generator-year observation. Let X_i be the observable states affecting transitions, s_i the operational state in year t, and u_i the operational state in year $t + 1$, decided in year t. The payoff function $g(X_i, s_i; u_i)$ describes the payoff the agent can expect in each discrete time step, and therefore how the rational agent should act. The agent's payoff depends on his current operational state and his choice about next period, as we assume that the transition to a new state starts halfway through the current year. This gives five possible transitions, OP-OP, OP-SB, SB-OP, SB-SB and SB-RE.

The generators utilize different fuels and have different heat rates. In addition, there are non-fuel variable maintenance and operational costs associated with being operational. The resulting day d spark spread for a specific generator n in an energy-only market (EO) can be expressed as follows:

$$S^{EO}_{n,d,t} = P^{e}_{n,d} - H_{n,t} * P^{f}_{n,d} - V_{n,t} \tag{1}$$

Here, $P^{e}_{n,d}$ is the daily on-peak (07-22) average zonal electricity price in \$/MWh for generator n on day d and $P^{f}_{n,d}$ is the generator n specific fuel price in \$/MMBtu for day d. $H_{n,t}$ is the heat rate for generator n in MWh/MMBtu in year t, and $V_{n,t}$ is the non-fuel variable operation and maintenance costs in \$/MWh for generator n.

For the energy-only formulation, the state process simply consists of the sum of nonnegative daily spark spreads. The generator-year specific state process is, in fact, a single state variable established in the following way:

$$X^{EO}_{n,t} = \sum_{d=1}^{T_t} max(S^{EO}_{n,d,t}, 0) * \left(\frac{16}{1000kW\,MW^{-1}}\right) \tag{2}$$

and has units \$/kWh-year. T_t is the number of days in year t.

The payoff function for the energy-only formulation is:

$$g(x,\ s;\ u) = \begin{cases} X^{EO}_{n,t} - M_{OP} & \text{if } s = \text{OP and } u = OP \\ \frac{1}{2} \cdot \left(X^{EO}_{n,t} - M_{OP} - M_{SB}\right) - K_{OP \to SB} & \text{if } s = OP \text{ and } u = SB \\ \frac{1}{2} \cdot \left(X^{EO}_{n,t} - M_{OP} - M_{SB}\right) - K_{SB \to OP} & \text{if } s = SB \text{ and } u = OP \\ -M_{SB} & \text{if } s = SB \text{ and } u = SB \\ -K_{RE} - \frac{1}{2} M_{SB} & \text{if } s = SB \text{ and } u = RE \end{cases} \tag{3}$$

The spark spread calculation for the capacity market formulation is similar to the energy only formulation but differ by the fact that capacity payments are included. Generators that clear the capacity auctions commit to one year of capacity delivery, and receive payments for each day of the delivery year. The spark spread calculation for the capacity model formulation becomes:

$$S^{CM}_{n,d,t} = P^{e}_{n,d} - H_{n,t} * P^{f}_{n,d} - V_{n,t} + P^{c}_{n,t} \tag{4}$$

where $P^{c}_{n,t}$ is the capacity price in year t in \$/MW-day, for generator n. The profitability measure becomes:

$$P^{CM}_{n,t} = \sum_{d=1}^{T_t} max(S^{CM}_{n,d,t}, 0) * \left(\frac{16}{1000kW\,MW^{-1}}\right) \tag{5}$$

In contrast to the energy-only formulation, we include other factors than the yearly sum of the spark spread in the state process. For the capacity market formulation the state process vector consists of the following elements, which all are thought to have an effect on the switching behavior through the payoff function.

$$X^{CM}_{i} = \{P^{CM}_{i}, C_i, R_i, P^{NG}_{i}\} \tag{6}$$

We use the subscript i to denote a generator-year observation. C_i is a variable measuring the competitiveness of a generator, R_i a dummy variable for environmental regulations and $P^{NG}{}_{i}$ the first order difference of the natural gas price. In contrast to P^{CM}, which represents a monetary amount per kW of capacity, the other elements are not directly implementable in the payoff function, because they have no obvious monetary interpretation. Therefore, we use the approach of Fleten et al. (2015) and use linear combinations of these elements to estimate switching costs. This is sensible because these factors are important exogenous processes that define the market conditions of the generator. When including them in the state process, we are able to account for changes in the generator's environment and better estimate the perceived risk of the agents.

The resulting payoff function has the following form ($\overline{X} = X^{CM}_{i} \setminus P^{CM}_{i}$):

$$g(x;\ s,\ u) = \begin{cases} P^{CM}_{n,t} - M_{OP} & \text{if } s = \text{OP and } u = OP \\ \frac{1}{2} \cdot \left(P^{CM}_{n,t} - M_{OP} - M_{SB}\right) - K_{OP \to SB}(\bar{X}) & \text{if } s = OP \text{ and } u = SB \\ \frac{1}{2} \cdot \left(P^{CM}_{n,t} - M_{OP} - M_{SB}\right) - K_{SB \to OP}(\bar{X}) & \text{if } s = SB \text{ and } u = OP \\ -M_{SB} & \text{if } s = SB \text{ and } u = SB \\ -K_{RE}(\bar{X}) - \frac{1}{2} M_{SB} & \text{if } s = SB \text{ and } u = RE \end{cases} \tag{7}$$

The rest of this section describes the elements of the state variable vector $\overline{X}$.

Inverse competitive advantage: The inverse competitive advantage reflects the relative competitiveness of a generator in comparison to its peers within the same transmission zone. Specifically, this is done through a comparison of the generator's heat rate to the average heat rate. Since PJM uses locational marginal pricing, we take all generators within a given zone as competitors, in contrast to Fleten et al. (2015), which define competition on a state level. Since electricity from peaking generators is a strictly homogeneous commodity, their only way to gain a competitive advantage is through increased efficiency. Hence, this variable will capture any technological advantage that one generator might hold over its competitors. We have:

$$C_{t,n} = \frac{H_{t,n}}{\bar{H}_{t,n}} \tag{8}$$

where $\bar{H}_{t,n}$ is the average heat rate of the competitors of generator *n* in year *t*.

Expectation of stricter environmental regulation: In Chapter 1, we describe the recent changes in environmental policy schemes, and how these will affect the market dynamics. We employ the binary variable R_t to capture these effects on the switching costs of the generators. We have

$$R_t = \begin{cases} 1 & \text{if } t \in [2002, 2003, 2010, 2011, 2012, 2013, 2014] \\ 0 & \text{else} \end{cases} \tag{9}$$

The main drivers of uncertainty regarding environmental policy schemes are the introduction of the CAIR, CSAPR and the NBP. The choice of values for t where Rt is set to 1 is based on judgement on how the policy discussions have affected the expectations of the decision makers. We argue that in these years, plant managers would expect the stricter regulations to be implemented, and thus that they are expected to act differently.

Change in natural gas price: In addition to the natural gas price information in the spark spread, we include the first order difference of the NG price time series as a separate state variable. We believe that the evolution of the natural gas price carries decision-relevant information that must be addressed because the NG market has changed profoundly. This variable will capture any change in perceived switching costs caused by the changes in the NG market. We have:

$$P_t^{NG} = \overline{P^{NG}}_t - \overline{P^{NG}}_{t-1} \tag{10}$$

where $\overline{P_t^{NG}}$ denotes the average gas price over year *t*. P_t^{NG} is positive in periods with increasing gas price, and negative if the gas price is falling.

Next, we display the results of the analysis. Table 3 shows the results from the estimation of the energy-only formulation for the period before the introduction of the RPM.

Table 3: Energy-only formulation for the period 2001-2007

	M_{OP}	M_{SB}	$K_{SB\to OP}$	$K_{OP\to SB}$	$K_{SB\to RE}$
Estimate $[\$/kW-year]$	9.127	0.409	1.911	0.436	-56.066
Significance level	1%	-	-	-	1%

We estimate positive maintenance costs in the operational state and standby state, with the standby maintenance cost being much lower. Both switching costs are positive, with a higher startup than shutdown cost. The retirement cost is negative and of far greater magnitude than the startup and shutdown costs. Using parametric bootstrapping, we find that only M_{OP} and $K_{SB\text{-}RE}$ are significant.

The sign and magnitude of the estimates for the energy-only formulation support the findings of Fleten et al. (2017). In this paper, the same model formulation is used to estimate costs for PJM, NYISO, and ISO-NE peaking units in the period between 2001 and 2009. The authors conclude that the estimates lie in the range of the true maintenance and switching costs. EIA estimate that the fixed O&M costs of a combustion turbine lie in the range between 6.70 and 6.98 $/kW ¡ year (U.S. Energy Information Administration, 2010). The retirement cost (i.e., scrapping value) is larger in our estimates than in the estimates of Fleten et al. (2017). The scrapping value will reflect the value of replacing an old unit with a newer one, as well as the second-hand value of the unit.

The capacity market formulation aims to better model the market dynamics after 2007, with the introduction of the RPM, the shale-gas revolution, and stricter environmental regulation. When interpreting the results, it is important to keep the numeric range of each variable in mind, to get a sense of the magnitude of impact. Table 4 present the range and average for the state variable vector X_i.

Table 4: Descriptive statistics for elements in the state variable vector

	P_i^{CM}	C_i	P_i^{NG}	R_i
Min	0	0.62	-4.92	0
Max	199.40	2.17	3.03	1
Average	37.42	1.00	-0.08	0.38

Estimates for the maintenance costs and switching costs between the different operational states for all generators in the data set are presented in Table 5. Significance levels from parametric bootstrapping are indicated with asterisks in parentheses.

Table 5: Capacity market analysis results

	Estimated value
M_{OP}	33.565 (***)
M_{SB}	0 (***)
$K_{SB\rightarrow OP}$	
Intercept	0
C_i	22.457
P_i^{NG}	2.074 (*)
R_i	-14.281 (***)
$K_{OP\rightarrow SB}$	
Intercept	1.233
C_i	-38.628 (**)
P_i^{NG}	-7.435 (***)
R_i	13.049 (***)
$K_{SB\rightarrow RE}$	
Intercept	-80.807 (***)
C_i	-69.147 (***)
P_i^{NG}	-1.465 (**)
R_i	10.155 (**)
Observations	10401
Note:	*p<0.1; **p<0.05; ***p<0.01

Maintenance cost

The estimate for the maintenance cost in the operating state, M_{OP}, is higher for the capacity market formulation than for the energy-only formulation, implying that the perceived costs of maintaining the turbine and generator in the operational state have increased in the years after 2007. The increased maintenance costs can be attributed to several factors. After the sudden drop in NG prices around 2008, peaking units became competitive not only in times of peak demand. They were dispatched more often, giving increased wear and tear on both the generator and the turbine. The stricter environmental regulations that were imposed on power generating units from 2010 have affected the maintenance cost.

The SB state maintenance costs are estimated to zero. In reality, there are costs associated with maintenance in the SB state. Power plants are subject to taxation on the plant site, equipment needs to be maintained, long-term rental contracts on buildings and equipment might run, etc. All these costs will be SB state maintenance costs for the plant owner. However, to explain the zero estimate for M_{SB}, we recognize that our model formulation allows two sets of equilibrium solutions. The first set of solutions assigns cost incurred in the standby state to M_{SB} and consequently estimates a startup cost $K_{SB\text{-}OP}$ at a moderate level. The results from the energy-only formulation in Table 3 adhere to this group of solutions. We believe that this group reflects reality most accurately. The other set of equilibrium solutions assigns costs incurred in the maintenance state to the startup cost estimate $K_{SB\text{-}OP}$ as a lump sum. This gives high startup costs, and low or zero SB maintenance costs, as seen in Table 5. When running parametric bootstrapping samples for the capacity market formulation, all results converged to the low or zero SB maintenance cost and high costs of startup equilibrium.

We conclude that the energy-only formulation better reflects the true maintenance costs in standby mode and that the changed market conditions introduce effects that we fail to control for in the capacity market formulation.

Intercepts for startup and shutdown costs are estimated to be zero. As long as we focus on the sign of the estimates and to a lesser degree focus on their magnitude when interpreting how they impact switching costs, the intercept is of less interest.

Startup cost, $K_{SB\text{-}OP}$

A positive coefficient for the inverse competitive advantage C_i implies that generators with a high value for C_i, equivalent to low fuel-to-electricity conversion efficiency, have a high perceived cost associated with starting up. This is as expected, as a generator performing worse than its competitors will have a higher barrier of entry into the market. This is consistent with real options theory predicting a high entry barrier for units with high costs. However, the coefficient is not significant in parametric bootstrapping and should be interpreted with this in mind.

As for the NG price development, P^{NG}_i, increasing natural gas prices implies higher costs of starting up. The cost of fuel is the most important driver of variable costs for a gas turbine. A minority of the turbines studied run on distillate fuel oils or kerosene, but there is a positive correlation of 0.134 between the NG and DFO prices. Therefore, we would still expect a positive sign for this coefficient. The coefficient is low, indicating that the gas price development has only a limited effect on the startup costs.

The effect of expectations to stricter environmental regulation, R_i, is not straightforwardly interpreted. At first glance, it seems intuitive that new, stricter, environmental regulation would increase the perceived cost of re-entering the market. Many generators must make investments to ensure compliance with the new regulations. For generators that are in SB mode when these regulations are expected to be implemented, these costs can be viewed as part of the startup cost.

However, there are effects working in the opposite direction. When new environmental regulation schemes are implemented, those affected usually have a few years to comply with the new rules—a grace period. A turbine that expects to be affected by new regulations might realize that it is better to stay operational until the regulations force it to retire. In other words, the value of waiting is significantly reduced as a consequence of the new regulations. If this is true, we would expect to see peaks of SB-OP transitions in the years before the introduction of new policy schemes. Looking at Figure 1, this is indeed the case.

It is also paramount to keep in mind that environmental regulations will hit all generators in the power market, not only peaking units. In fact, much old coal-fired baseload capacity will be forced to retire (Institute of Energy Research, 2013). This will create a capacity deficit that makes it more attractive for gas turbines to go into operation. The attractiveness of this option is enhanced by the favorable development in the natural gas price. A negative and highly significant coefficient for the environmental regulation coefficient suggests that these effects dominate how new environmental regulations affect startup costs.

Shutdown cost, $K_{OP\text{-}SB}$

Analogous to the effect on startup cost, increased inverse competitive advantage C_i gives lower perceived costs of shutdown, as the market favors efficient units. A positive development in the NG price reduces the cost of shutdown. When NG prices rise, it becomes more expensive to run the generator and the perceived cost of entering standby mode drops.

The expectations to stricter environmental regulation variable, R_i, is positive, meaning that we see the same dynamic for the shutdown cost as we did for the startup cost. Generators seem to recognize the vacuum left by retiring coal-fired baseload and therefore see a substantial opportunity cost of switching away from the operational state when new regulations are expected. The coefficient is of similar magnitude and significance as for the startup cost.

Retirement cost, $K_{SB\text{-}RE}$

The intercept of the retirement estimate is negative and can be seen as a baseline monetary estimate of the scrap value for the generators. This can be attributed to the secondhand value of the machinery and the opportunity cost of freeing space, labor and capital that has been tied to the operation of the turbine or replacing the unit with a new one.

The coefficient for the inverse competitive advantage is negative and large in magnitude, implying that a reduction in competitiveness leads to an increase in perceived scrapping value. We recognize that this result is somewhat puzzling. However, part of the effect can be explained by the higher value of freeing space, labor, and capital held up in a less competitive plant.

The scrapping value increases when the gas price is increasing. It is more favorable to scrap the turbine when the variable costs increase, which makes sense in a situation where the plant manager has to choose between staying in standby and retiring the plant. Re-entering the market would be economically irrational in a situation with increasing natural gas prices, at least for generators running on NG3. From real options theory it is known that when in a mothballed state, the agent should wait until the spark spread either picks up to the entry barrier or drops to the barrier where abandonment is the best option (Dixit and Pindyck, 1994). From this perspective, it is reasonable that the perceived value of scrapping the turbine increases when the natural gas price drops closer to the abandonment barrier.

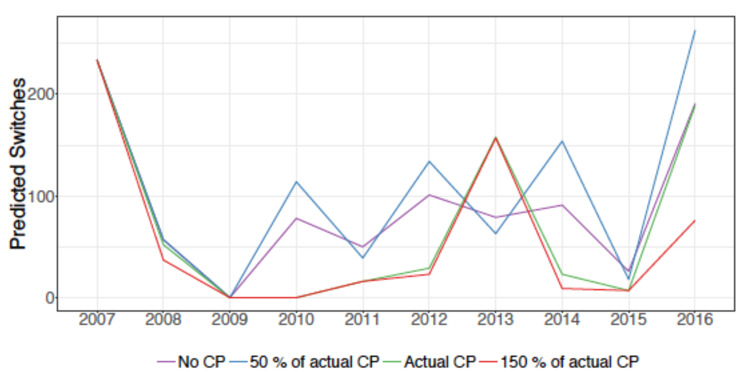
In years where it is expected that new environmental regulation will be implemented, we see that the scrapping value is reduced since the regulatory schemes also affect generation units in the second-hand market. This effect seems to outweigh the value of freeing space, labor and capital for alternative use.

Counterfactual analysis

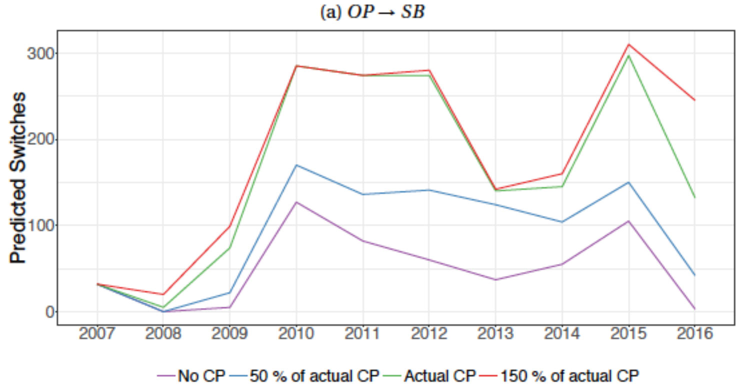
RPM introduced capacity remuneration to ensure adequacy in the power system. A key issue in such a market scheme is to set the appropriate level of compensation. Too much compensation might induce too much investment, and too low levels will not give sufficient investment signals. In our counterfactual analysis, we construct scenarios by lowering and upping the capacity payments from the observed levels in our data.

Figure 2 shows the switching behavior under different capacity payment (CP) scenarios as predicted by the counterfactual model. The predictions show less switching and more plants staying in OP when capacity payments are high. This is in line with the regulator's goal of having generators ready to deliver energy when needed.

For the switching behavior predicted in Figure 2a, we see that reducing the capacity payments lead to increased switching and increasing the capacity payments reduces switching. The effect of reducing the capacity payment level is much greater than the effect of a corresponding increase in capacity payments. The reduction in switching activity under higher capacity payment levels leads to more plants staying operational, as seen in Figure 2b.



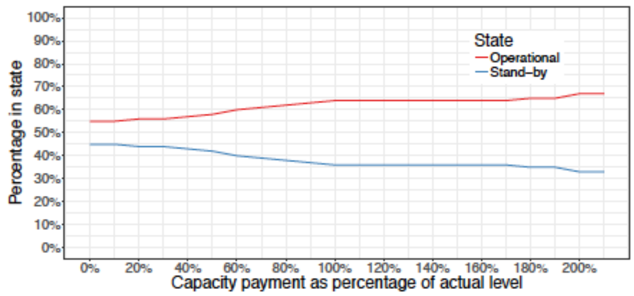
(a) $OP \rightarrow SB$



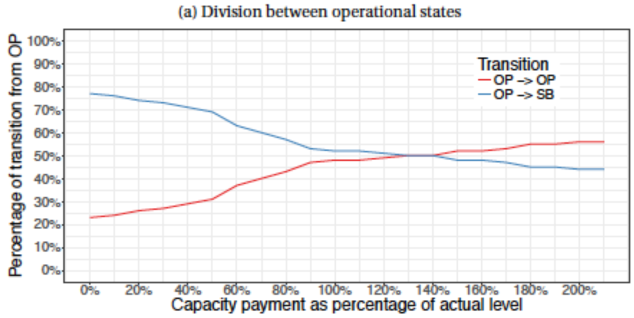
(b) $OP \rightarrow OP$

Figure 2: Counterfactual analysis on switching behavior from OP

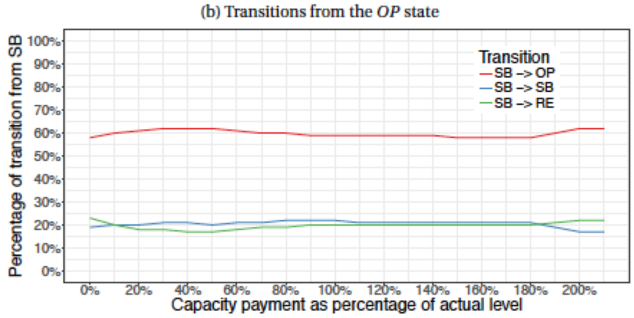
Figure 3 plots the result of a sensitivity analysis on the capacity payment levels in the counterfactual model. Figure 3a shows that increased capacity payments lead to an increase in the share of plants staying in OP state. Broken down to switches for plants currently in the operational state, Figure 3b clearly illustrates that the higher the capacity remuneration, the more attractive it becomes to stay in the operational state. The sensitivity analysis shows that the generators are most sensitive to changes in capacity payments when the payments are 50%-90% of the empirically observed level. Figure 3c shows that the switching behavior from the SB state is unaffected by the level of capacity payments. However, fewer plants switch away from OP as capacity payments increase. The means that there are fewer plants in the SB state as capacity payments increase. This mechanism explains the development in Figure 3a.



(a) Division between operational states



(b) Transitions from the *OP* state



(c) Transitions from the *SB* state

Figure 3: Sensitivity analysis of capacity payments

Conclusions

We find evidence that market conditions for peaking units in the PJM has changed significantly after 2007, and identify three market trends influencing the behavior of peaking units. Technological advancements have changed the supply side of the natural gas market, giving a persistent drop in fuel prices for gas-fired turbines. New environmental regulations have forced old coal-fired baseload into retirement, presenting new market opportunities for gas-fired units. We also see that the regulations have led to the retirement of old combustion turbines. The introduction of capacity payments has led to less switching and a higher amount of peaking plants being ready to operate.

The first trend, the penetration of shale gas in the US gas market, significantly reduced the fuel price for many generators. We conclude that this has disrupted the traditional market dynamics where coal-fired plants serve as baseload, and combustion turbines cover peak demand. Gas-fired turbines have become more competitive in serving baseload, and besides, traditional baseload has been punished harder by stricter environmental regulations than gas units. Consequently, peaking units are now dispatched more often, increasing the wear and tear on the mechanical equipment. This is a plausible explanation for the increase in the estimated maintenance cost for generators after 2007. The second effect that influences the switching behavior of peak generators is the introduction of stricter environmental regulation schemes. In years where regulatory changes are expected, our estimates show that the perceived cost of startup decreases and the perceived cost of shutdown increases. This tendency to prefer to operate in years with new regulations must be seen in light of the fact that environmental regulations are imposed on all actors in the power market. Coal-fired baseload is more polluting than most other technologies and is therefore affected more severely by stricter environmental regulations. Gas is cleaner, has become cheap, and gas plants are quick to bring online. This makes it possible for gas-fired units to replace the retiring coal-fired baseload, a fact reflected in the environmental regulation coefficient estimate.

Finally, after the introduction of the RPM, less switching is observed, and the share of operational peaking generators is larger, with few generators being in the standby state. The results from the counterfactual analysis indicate that the switching behavior is affected by the level of the capacity payments. Lowered capacity payments will give more switching, whereas increased payments cause minimal change. Overall, our findings indicate that the system operator is successful in incentivizing peaking generators to stay in an operational-ready state through capacity payments.

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