NTNU
Norwegian University of
Science and Technology

Analyzing the Effect of Capacity Payments on Peaking Generator Operation

Magne Eie Ledsaak
Sigurd Bondahl Mehl
Ola Esten Røssum

Industrial Economics and Technology Management
Submission date: June 2018
Supervisor: Stein-Erik Fleten, IØT

Norwegian University of Science and Technology
Department of Industrial Economics and Technology Management

Problem description

We study the effects of capacity payments on the operational decisions of plant managers for peaking units in the Pennsylvania-New Jersey-Maryland (PJM) Interconnection. During the period under study, the market environment for peaking units has changed profoundly, and we assess the impact of these changes on startup, temporary shutdown, and retirement decisions, as well as the costs associated with these switches.

Preface

This thesis concludes our integrated Master of Science in Industrial Economics and Technology Management at the Norwegian University of Science and Technology.

We would like to thank our supervisor Professor Stein-Erik Fleten for his guidance and valuable insight. Also, we would like to express our gratitude to Associate Professor Carl Ullrich at James Madison University and PhD Research Scholar Benjamin P. Fram at the Norwegian School of Economics for their help in understanding the US power markets. They have provided invaluable insight into the topic at hand both in emails and through Skype meetings.

Trondheim, 01-06-2018

Magne Eie Ledsaak

Sigurd Bondahl Mehl

Ola Esten Røssum

Abstract

This thesis aims to study the effects of capacity payments on the operational decisions of plant managers for peaking units in the Pennsylvania-New Jersey-Maryland Interconnection (PJM). 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. Capacity markets are introduced as a means of compensating capacity, and 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.

Sammendrag

Denne oppgaven tar sikte på å studere hvordan kapasitetsutbetalinger påvirker operasjonelle beslutninger for topplastkraftverk i Pennsylvania-New Jersey-Maryland Interconnection (PJM). Vi utfører en strukturell estimering av vedlikeholdskostnader, samt overgangskostnader mellom operasjonell modus, midlertidig nedstengt modus og permanent nedstengt modus. Vi studerer årene fra 2001 til 2016, fordi dynamikken i kraftmarkedet endrer seg betraktelig i denne perioden. Videre foretar vi en kontrafaktisk analyse av nivået på kapasitetsbetalinger for å undersøke effekten av å innføre et kapasitetsmarked i 2007. Fleksible topplastkraftverk er avgjørende for kraftsystemets pålitelighet i perioder med høy etterspørsel. Forståelse av de reelle kostnadene av å eie og drifte slike enheter er avgjørende for å utarbeide markedsregler som sikrer tilstrekkelig kapasitet i kraftsystemet. Kapasitetsmarkeder er innført for å kompensere tilgjengelig kapasitet. I oppgaven vår analyserer vi hvordan slike marked påvirker topplastkraftverkenes veksling mellom operasjonell og midlertidig nedstengt tilstand.

Fra de empiriske dataene våre fremgår det at vekslingsaktiviteten avtar etter at kapasitetsbetalinger ble innført. Rollen topplastkraftverk fyller i markedet har endret seg ved at enhetene produserer oftere. Den kontrafaktiske analysen viser en klar sammenheng mellom nivået på kapasitetsutbetalinger og hyppigheten av veksling mellom operasjonell og midlertidig nedstengt modus. Vi konkluderer med at dagens nivå på kapasitetsutbetalinger i PJM gir topplastkraftverk insentiv til å holde seg i operasjonell tilstand.

Contents

Appendices

List of Figures

List of Tables

Chapter 1

Introduction

The fundamental task of maintaining an adequate and reliable power supply in a power system requires low variable cost baseload and flexible peak generation units. Historically, in the US power system, the baseload generation capacity has consisted mainly of nuclear and coal power plants. However, the development in recent years has shown increased participation of both combustion turbines and renewables to serve as baseload generation.

Peak generating units must be highly flexible and controllable with short response time to be able to pick up the ever-fluctuating demand on both an intraday and a seasonal basis. 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. Combustion turbines are currently the technology best suited for this role.

Electricity cannot be stored like other commodities, resulting in the fact that supply and demand of electricity have to match instantaneously. This gives rise to two demand-side market flaws making the electricity market different from other commodities markets (Stoft, 2002). Firstly, the lack of metering and real-time billing of consumers makes demand inelastic, as the consumers cannot see the cost of the electricity they consume in real time. Secondly, there is no way to monitor the exact flow of electricity, making it hard to allocate cost to individual consumers. Because of these flaws, the market is unable to set a price on electricity in times of scarcity. If the market were efficient, it would match supply and demand at the price consumers are willing to pay, hence covering the total cost of production for suppliers. In the presence of the market flaws, the system operator (SO) needs to intervene and set a price that balances the consumers' willingness to pay against the suppliers need for sufficient compensation to uphold the production capacity required.

When the demand for electricity is less than the total generation capacity, the SO cost-effectively matches supply and demand by merit order dispatching. Merit order dispatching entails that the generating units are ordered ascendingly based on their short-run marginal cost of production so that the least costly units are dispatched first. This means that units with high short-run marginal costs risk not being dispatched. The marginal unit, i.e., the unit producing the last incrementally demanded amount of electricity, sets the market price for the entire market. Other dispatched units earn the scarcity rent, which amounts to the compensation received beyond their short-run variable cost of production. In effect, if the demand were constant at a certain level, the marginal producing unit would never be able to cover the fixed cost of the generator and would be forced to retire.

There are different strategies for compensating generation units. Most commonly, generators are compensated only through payments for the electricity that they deliver into the power system. A power system that relies solely on this compensation procedure is called an energy-only market. In recent years, in addition to compensating for the electricity delivered, some power markets have started compensating generators for the capacity that they can deliver into the power system. This means that a generator can receive compensation based on a commitment to offer capacity in the future. Some, such as Oren (2005) and Hogan et al. (2005), argue that such capacity remuneration mechanisms should be unnecessary in power markets and that generating units should be able to cover their fixed costs by bidding higher than their short-run marginal costs in the auctions during shortage periods. Cramton and Stoft (2005), however, conclude that the power market imperfections always will be present, and that capacity remuneration mechanisms can be needed to ensure adequacy and reliability in times of shortage.

In an energy-only market, the fixed cost of the peak generators must be covered through high price spikes, often capped by the SO. In cases where demand exceeds supply, the price skyrockets because of a near vertical supply curve and it is the job of the SO to set an appropriate price cap. This is when the marginal producer will be compensated in excess of short-run marginal cost. Setting this price cap appropriately is inherently difficult, but crucial to create effective investment incentives, especially for peaking units that are only producing when demand is high. 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. In theory, the energy prices in a capacity market are lower than in an equivalent energy-only market as part of the compensation is done through the capacity payments. This can lead to a more stable energy price environment with lower price caps in times of scarcity.

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. 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 1.1 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

[1] Generators are not allowed to bid in their nameplate capacity, as generator outages must be accounted for.

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 1.1: 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 NO_x 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 (NO_x) and sulfur dioxide (SO_2). 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.

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. As a consequence, the price of natural gas dropped significantly after 2008, as seen in Figure 2.2c, 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 gen-

[2] Demand response is the mechanism where consumers are financially compensated for reducing load in peak hours.

[3] Numbers from the US Energy Information Administration.

erators. 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.

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. Also, 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.

In the literature, the estimation of parameters in structural models and dynamic games of entry and exit is given much attention. 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) and 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 new computational method; a Mathematical Program with Equilibrium Constraints (MPEC). Here, the problem is solved as a constrained optimization problem, 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. (2015, 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. (2015) 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.

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.

In this thesis, we use a structural model to estimate the switching costs of peaker generators in the PJM Interconnection with capacity payments and account for other major exogenous factors. We observe a different pattern of switching activity after the introduction of the RPM and employ our 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. Structural estimation of cost structures in power markets with capacity payments is as far as we know new to the literature. 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.

The rest of this thesis is outlined as follows. Chapter 2 introduces the data used in the structural estimation. Chapter 3 describes the decision problem for the plant managers and introduces the model formulations as well as the methodology for the counterfactual analysis. Chapter 4 presents and discusses the results from the structural estimations for the model formulations. Chapter 5 presents the findings from the counterfactual analysis and evaluates how the level of capacity payments influence switching behavior. Chapter 6 concludes the findings of this thesis.

Chapter 2

Data

2.1 Data sources

We analyze data on PJM peaking generators from 2001 until 2016, extending the time frame of Fleten et al. (2015, 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.

2.1.1 Observed switching

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.

2.1.2 Heat rate

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.

2.1.3 Variable operating and maintenance costs

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[1].

2.1.4 Time series data

The time series for historic peak hour[2] electricity and capacity prices are collected from PJM's database. There are significant transmission constraints within the transmission

[1] VOM estimates for new plants in the EIA assumptions documents for different years vary substantially from year to year, but we see the general trend that old plants have higher VOM.

[2] The 16-hour interval from 06:00 to 22:00.

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. Figure 2.2 shows the development of the time series used for calculation of the profitability indicator.

2.2 Construction of spark spread profitability measure

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[3]. Therefore, we incorporate the capacity

[3]These assumptions are established in discussion with Benjamin J. Fram, PhD Research Scholar at the Norwegian School of Economics, Department of Business and Management Science, and former Power Market Analyst at Monitoring Analytics in the Greater Philadelphia Area.

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.

2.3 Description of data set

2.3.1 Observed switches and profitability

Table 2.1: 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***
	Number of observations	3479	64	161	755	76
2001-2007	Share	98.2 %	1.8 %	16.2 %	76.1 %	7.7 %
	Average profitability	12.28	5.85	14.25	13.00	5.58
	Number of observations	4435	4	15	521	32
	Share	99.9 %	0.1 %	2.6 %	91.7 %	5.6 %
2008-2016	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

Table 2.1 shows the possible transitions as well as the number of observed transitions and the corresponding average profitability. 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 2.1, 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 non-economical 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 2.1 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 ac-

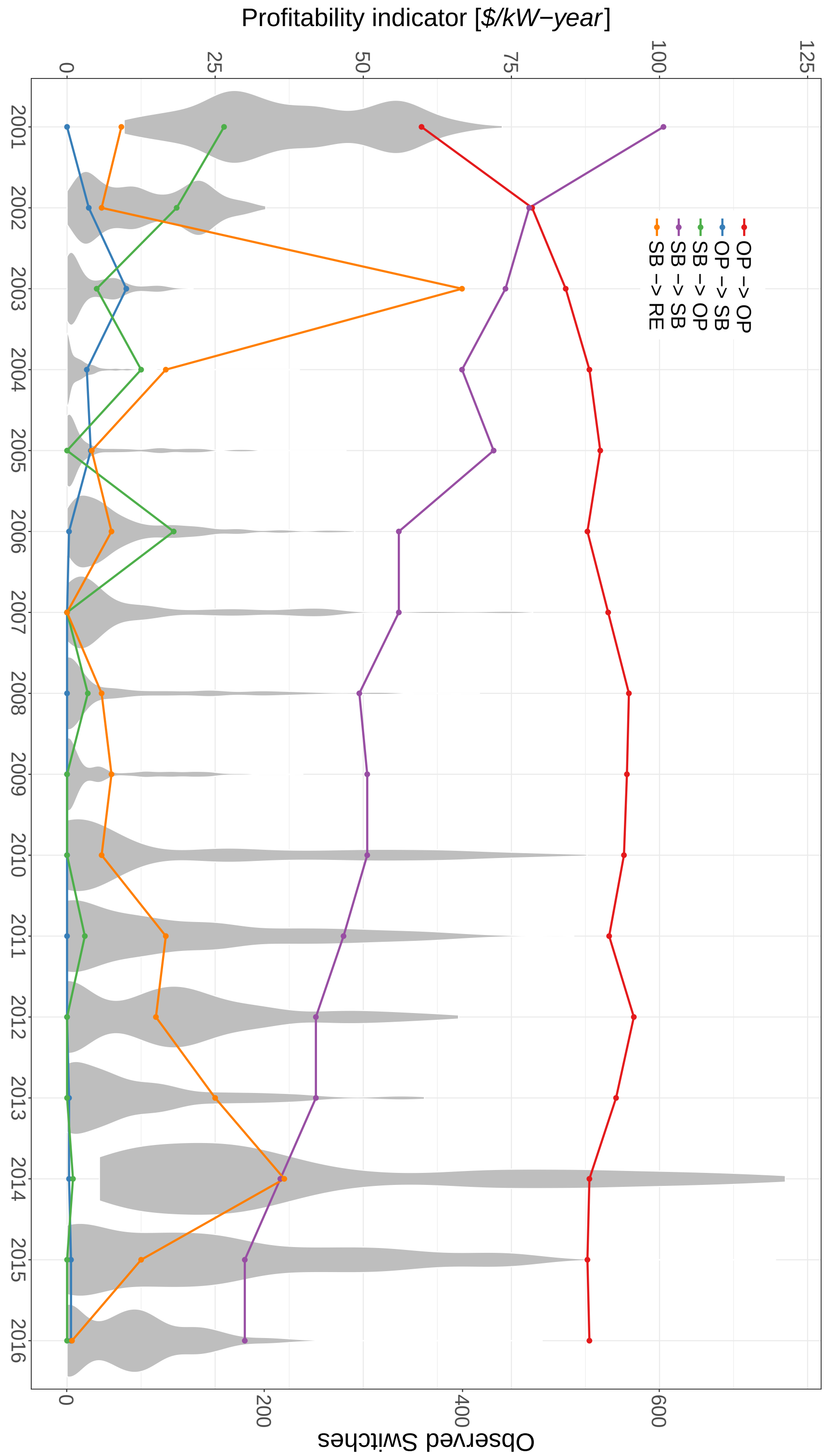


Figure 2.1: Observed switching behavior and distribution of the energy-only profitability indicator

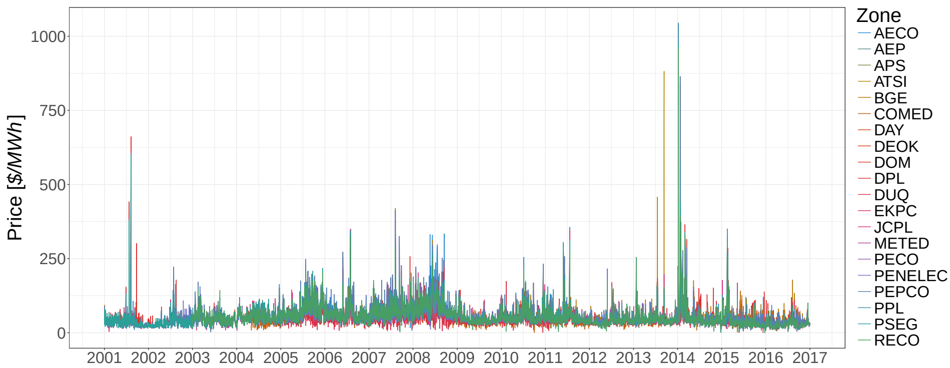
cordance with the profitability indicator. In an environment driven mainly by revenue from delivering energy into the power system, one would expect that switching behavior is strongly related to the development in the profitability indicator. In relative terms, there are more switches from the standby state to operating state ($SB \rightarrow OP$) 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 ($OP \rightarrow SB$) 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 between 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.

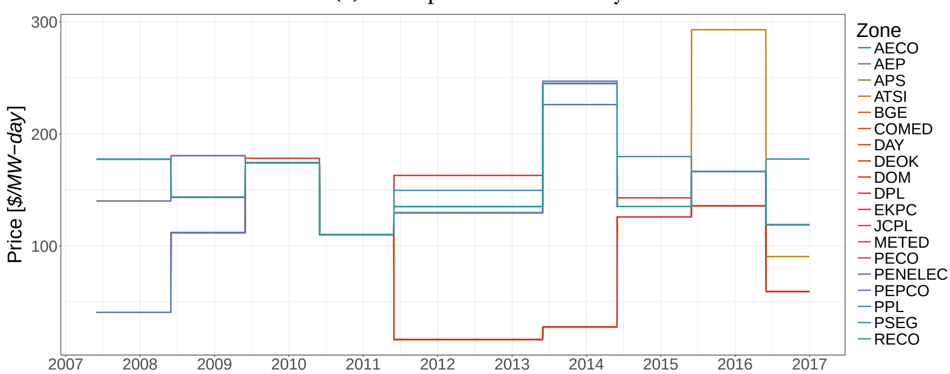
For the fuel prices, we can see signs of a new regime after 2007, as illustrated in Figure 2.2c. The natural gas price stabilizes at a lower level, and recognizing that natural gas is used as fuel for approximately 65% of the generators in our dataset, this development is likely to be the main driver of the improved energy-only profitability seen for the plants in the period after 2009.

Figure 2.3 illustrates how the switching behavior relates to the development of the energy-only profitability measure from one year to the next[4]. We gain insight into the relationship between profitability measures for the individual generator-year observations and the corresponding transition observed. We clearly see that switches from OP to SB and SB to RE, colored orange and red respectively, happen for lower pairs of the profitability indicator than the more optimistic switch from SB to OP.

[4]Note once again that capacity payments are excluded for illustrative purposes. In addition, all of the observations along the center line are observations from 2016. There is no data for 2017, so 2016 values were assumed.



(a) Zonal prices for electricity



(b) Zonal prices for capacity

(c) Fuel prices

Figure 2.2: Time series used for profitability indicator calculations

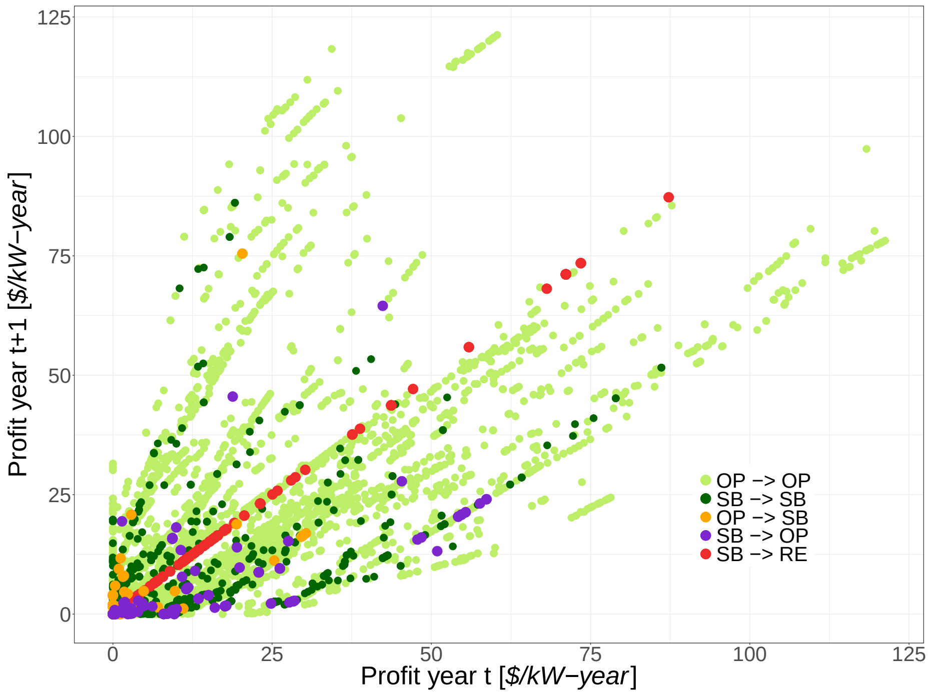


Figure 2.3: Scatter plot of profitability and switching

2.3.2 Retirement observations

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.

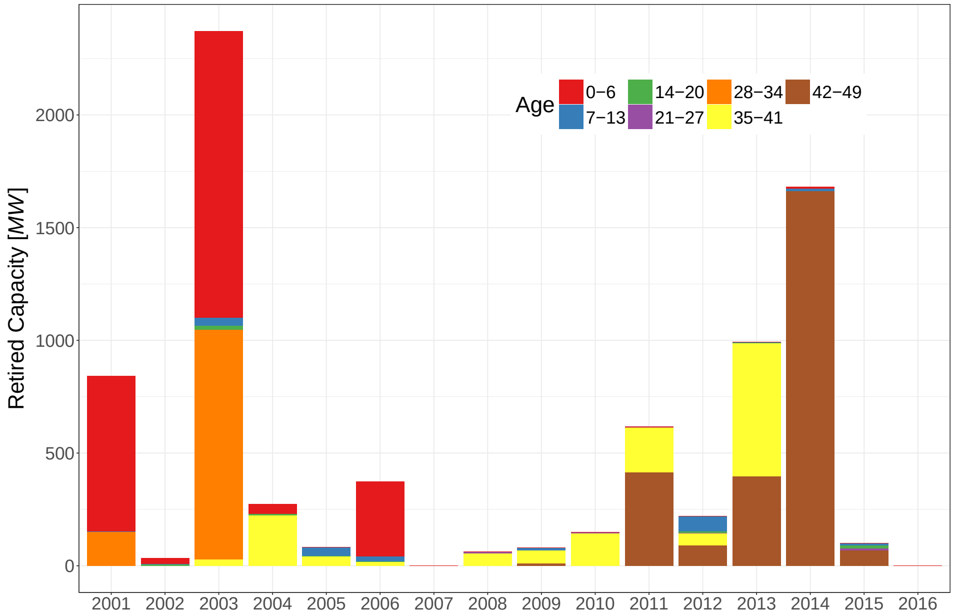
The second driver mentioned by the PJM concerns the environmental regulations that have been introduced during the period of study. The spike of retirements seen in 2003 must be considered in relation to the introduction of the NO_x Budget Trading Program (NBP) in this year. A NO_x emission scheme will punish older units more than more newer ones, as designs have been improved to reduce emissions (Lefebvre and Ballal, 2010). Also, there are more retirements seen in the period after 2011. In this period, CAIR was active and later replaced by the CSAPR. Limitations on SO_2 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, as seen in Figure 2.4. Figure 2.4a illustrates the age at retirement for the retiring capacity. We see that 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.

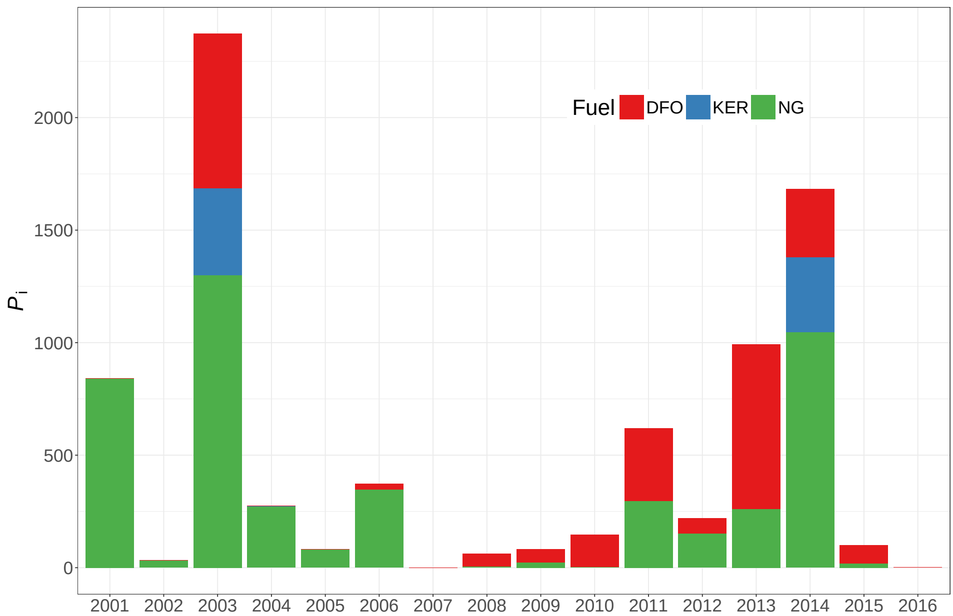
We see the same effect in Figure 2.4b, with a very high proportion of retiring capacity running on DFO and KER[5], which are dirtier fuels than NG. These observations point us in the direction that the retirements seen after 2007 can be explained by it becoming less favorable to operate older, dirtier 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, 2015) has not recognized this connection between retirements and environmental policy changes.

[5] Keep in mind that the total share of DFO and KER units in our data set is low, compared to NG.



(a) Retired capacity by age



(b) Retired capacity by fuel

Figure 2.4: Observed retirements

Chapter 3

Modelling approach

3.1 The agent's decision problem

As discussed in Chapter 1, 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.

The model is written in AMPL, based mainly on code kindly provided by our supervisor

Stein-Erik Fleten. The model formulation originates from Fleten et al. (2017) and has later been modified by Marius Johansen in his master thesis (Fleten et al., 2015). We use the KNITRO solver, an optimization software library primarily built for solving large-scale, continuous, non-linear mathematical optimization problems.

Firstly, in Section 3.1.1, we will present the general formulation of the agent's decision problem. This formulation represents a common framework for the energy-only and the capacity market formulations. Thereafter, in Section 3.2, we present the general optimization model. Finally, in Section 3.3, we take a closer look at how the two model formulations differ.

3.1.1 The real options formulation of the agent's decision problem

Table 3.1: Nomenclature for dynamic discrete-choice model

Symbol	**Description**
t	Time index; time unit is one year.
X_t	State process, publicly observed.
ϵ_t	Information not observable for researcher.
S	Set of possible states: $\{OP, SB, RE\}$.
$s_t \in S$	Operational state in year t.
$u_t \in S$	Operational state in year $t+1$, decided in year t.
$g(x,s;u)$	Net profit function.
$V\left(x,s\right)$	Value function.
$v(x,s)$	Expected (s-alternative specific) value function.
$\beta \in (0,1)$	Discount factor.

The agent's decision problem can, as briefly discussed in Chapter 1, be modeled as a Markov Decision Process. Such processes have two variable categories; state variables x_t and decision variables s_t. The agent's payoff function can be formulated by letting a set of primitives represent the agent. Further, we let a transition function $\{X_t, s_t; u\}$ represent the agent's belief about uncertain future stages and let β be the discount factor. A plant in the operational state will choose to produce only in times where the spark spread is positive. Assuming the agent to be fully rational, the expected value of owning a generator can then be viewed as a series of daily call options on the spark spread. Thus, we can study the agent's decision problem using a real options framework. The Bellman equation of the problem is developed below following Fleten et al. (2017):

$$V(x,s) = \max_{s_t=s_t(x_t)} \mathbb{E}\left(\sum_{t=0}^{\infty}\beta^t g(X_t, s_t; s_{t+1})\middle| X_0 = x\right) \tag{3.1}$$

$$= \max_{s_t=s_t(x_t)} \mathbb{E}\left(g(X_0, s_0; s_1) + \beta\cdot\mathbb{E}\left(\sum_{t=0}^{\infty}\beta^t g(X_{t+1}, s_{t+1}; s_{t+2})\middle| X_1 = x_1\right)\middle| X_0 = x_0\right) \tag{3.2}$$

$$= \max_{u\in S} g(x,s;u) + \beta\cdot\mathbb{E}\big(V\big(X_{t+1},u\big)\big|X_t = x\big) \tag{3.3}$$

Equation 3.3 defines an optimal decision rule for choosing the operating state, u_t, of the plant for the next operation period. Equation 3.3 cannot be solved using non-linear regression techniques for three reasons. Firstly, our dependent variable u is discrete. Secondly, the form of the optimal decision rule is not known and needs to be estimated. Thirdly, there will be information available to the agents that is non-observable to the researcher. This will however need to be accounted for in the problem formulation in the form of a stochastic term ϵ (Rust, 1994). It will be non-additive, non-separable, possibly multi-dimensional and carry additional, non-observable information concerning the transitions $u_t \in S$. In our case, ϵ will account for plant owners' private information. The private information held by the agents is an important source of uncertainty in the model. To incorporate the private information of the agents, we reformulate Equation 3.3:

$$V(x,\epsilon,s) = \max_{u\in S} g(X,\epsilon,s;u) + \beta\cdot\mathbb{E}\left(\int V\big(X_1,\epsilon_1,u\big)\mathscr{E}\big(d\epsilon_1\big|X_1\big)\middle|X_0 = x\right) \tag{3.4}$$

We define the last part of Equation 3.4 as the s-alternative specific value function

$$v(x,s) = \mathbb{E}\left(\int V\big(X_1,\epsilon_1,u\big)\mathscr{E}\big(d\epsilon_1\big|X_1\big)\middle|X_0 = x\right) \tag{3.5}$$

which is the average of the value functions V of all agents operating in the market.

Now the Bellman equation (3.3) can be rewritten in a way that incorporates private information:

$$V(x,\epsilon,s) = \max_{u\in S} g(x,\epsilon,s;u) + \beta\cdot v\big(x,u\big) \tag{3.6}$$

As proposed by Rust (1987), we need to impose two additional restrictions on our primitives, namely that ϵ enters the state process in an additive separable way and that the stochastic component is conditionally independent. Consequently, our payoff function can be separated in the following way:

$$g(x,\epsilon,s,u) = g(x,s,u) + \epsilon_u \tag{3.7}$$

Using the property of additive separability expressed in Equation 3.7, we rewrite $v(x,s)$ as:

$$v(x,s) \;=\; \mathbb{E}\bigg(\int \max_{u\in S} g(X_1,s;u) + \epsilon_{1,u} + \beta\cdot v\big(X_1,u\big)\mathscr{E}\big(d\epsilon_1\big)\bigg| X_0 = x\bigg) \tag{3.8}$$

Following extreme value theory the maximization in Equation 3.8 will converge to an extreme value distribution. Because the Gumbel distribution is the only extreme value distribution with two-sided support, and the ϵ is assumed to have the property of additive separability, ϵ will follow a process of mutually independent Gumbel distributed variables. Now, following the general lines of McFadden et al. (1973) and following Fleten et al. (2017), we rewrite our Bellman equation and solve it under the assumption that ϵ is a process of mutually independent Gumbel variables, which also are independent of the state process. Under the above conditions, the expectation can be simplified by using the property that the Gumbel distribution is closed under maximization:

$$\int \max_{u\in S}\big(\epsilon_u + c_u\big)\mathscr{E}\big(d\epsilon_u\big) = b\cdot log\bigg(\sum_{u\in S} exp\frac{c_u}{b}\bigg) \tag{3.9}$$

By defining $c_u = g(x,\epsilon,s;u) + \beta\cdot v\big(x,u\big)$ and applying Equation 3.9 to Equation 3.8 we arrive at:

$$v(x,s) \;= \mathbb{E}\;\bigg(\,b\cdot log\,\bigg(\sum_{u\in S} exp\,\bigg(\frac{g(X_1,s;u) + \beta\cdot v\big(X_1,u\big)}{b}\bigg)\bigg)\,\bigg|\,X_0 = x\,\bigg) \tag{3.10}$$

Here, b is a scale parameter, that can be interpreted as the degree of uncertainty about the decision of agents in situations where they have the same information when deciding (Fleten et al., 2017).

3.2 Optimization model for parameter estimation

The estimation of primitives is done by solving the maximum likelihood problem below (Rust, 1987; Su and Judd, 2012):

$$\begin{aligned} \text{maximize} \quad & \mathscr{L}\left(g, v_g, (X_i, s_i, u_i)_{i=1}^{N}\right) && (3.11) \\ \text{subject to} \quad & g \in G && (3.12) \\ & v_g = t_g(v_g), && (3.13) \end{aligned}$$

Here, i denotes a generator-year observation and N is the number of generator-year observations. $\mathscr{L}$ is the likelihood of observing the observed data $(X_i, s_i, u_i)_{i=1}^{N}$, and is restricted by the payoff function $g(\cdot) \in G$, where G is the set of possible profitability functions for a generator. The second constraint is a fixed point equation for the expected s-alternative specific value function, see Equation 3.10. Because of private information that is unobservable to the analyst, the decision for a given state (x, s) is not deterministic, but given by a choice probability

$$P_v(u \,|x, s) = \frac{exp\left(\frac{g(x,s;u)+\beta v(x,u)}{b}\right)}{\sum_{u'} exp\left(\frac{g(x,s;u')+\beta v(x,u')}{b}\right)} \tag{3.14}$$

determined by the fact that ϵ follows the Gumbel distribution. Hence, the objective function becomes:

$$\mathscr{L}\left(g, v(X_i, s_i, u_i)_{i=1}^{n}\right) = \prod_{i=1}^{N} P_v(u_i \big| X_i, s_i), \tag{3.15}$$

For a more thorough explanation of the optimization problem, we refer to Fleten et al. (2017), where the above problem formulation is presented more in-depth.

As briefly discussed in Chapter 1, we use the MPEC algorithm of Su and Judd (2012) to estimate the primitives. For our purposes, the MPEC is far less computationally demanding than if we were to use the NFXP of Rust (1987) because the NFXP would require us to solve the constraint $v_g = t_g(v_g)$ to optimality for each iteration as it enters the objective function. By using the MPEC algorithm, the constraint must only be satisfied for the last iteration of the algorithm.

3.3 Model formulations

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, $OP \rightarrow OP$, $OP \rightarrow SB$, $SB \rightarrow OP$, $SB \rightarrow SB$ and $SB \rightarrow RE$. In the following, we present how the two model formulations differ.

3.3.1 Energy-only formulation

A generator in the operational state in an energy-only market will be compensated for the energy it produces according to the price in the specific zone it is located within. 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:

$$S^{EO}_{n,d,t} = P^{e}_{n,d} - H_{n,t} * P^{f}_{n,d} - V_{n,t} \tag{3.16}$$

Here, $P^{e}_{n,d}$ is the daily zonal electricity price[1] 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 non-negative daily spark spreads. The generator-year specific state process is, in fact, a single state variable established in the following way:

$$X^{EO}_{n,t} = \sum_{d=1}^{T_t} max(S^{EO}_{n,d,t}, 0) * \left(\frac{16}{1000kWMW^{-1}}\right) \tag{3.17}$$

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

[1] Averaged over the 16 peak hour interval from 7 am to 10 pm.

The payoff function for the energy-only formulation is:

$$g(x,\ s;\ u) = \begin{cases} X_{n,t}^{EO} - M_{OP} & \text{if } s = \text{OP and } u = \ OP \\ \frac{1}{2}\cdot\left(X_{n,t}^{EO} - M_{OP} - M_{SB}\right) - K_{OP\rightarrow SB} & \text{if } s = OP \text{ and } u = \ SB \\ \frac{1}{2}\cdot\left(X_{n,t}^{EO} - M_{OP} - M_{SB}\right) - K_{SB\rightarrow OP} & \text{if } s = SB \text{ and } u = \ OP \\ -M_{SB} & \text{if } s = SB \text{ and } u = \ SB \\ -K_{RE} - \frac{1}{2}M_{SB} & \text{if } s = SB \text{ and } u = \ RE \end{cases} \tag{3.18}$$

The payoff function depends on the agent's choice of operational state u in the next period. In general we associate three different elements with the payoff function:

1. Profitability from participating in the electricity market, $X_{n,t}^{EO}$.
2. Maintenance costs in the operating state (M_{OP}) and stand-by state (M_{SB}).
3. Switching costs associated with shutdown ($K_{OP\rightarrow SB}$), startup ($K_{SB\rightarrow OP}$) or abandonment ($K_{SB\rightarrow RE}$).

The estimates of maintenance and switching costs should not be interpreted solely as monetary estimates, as any perceived risk associated with the transitions is factored into the estimates.

3.3.2 Capacity market formulation

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:

$$S_{n,d,t}^{CM} = P_{n,d}^{e} - H_{n,t} * P_{n,d}^{f} - V_{n,t} + P_{n,t}^{c} \tag{3.19}$$

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

$$P^{CM}_{n,t} = \sum_{d=1}^{T_t} max(S^{CM}_{n,d,t}, 0) * \left(\frac{16}{1000kWMW^{-1}}\right) \tag{3.20}$$

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.

$$X^{CM}_i = \{P^{CM}_i, C_i, R_i, P^{NG}_i\} \tag{3.21}$$

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[2] 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. We refer to these variables as the subset $\bar{X}^{CM}_t \subset X^{CM}_t$, so that

$$\bar{X}^{CM}_i = \{C_i, R_i, P^{NG}_i\} \tag{3.22}$$

[2] We scale the capacity payments to arrive at the correct units.

The resulting payoff function has the following form:

$$g(x;\ s,\ u) = \begin{cases} P^{CM}_{n,t} - M_{OP} & \text{if } s = \text{OP and } u = \ OP \\ \frac{1}{2} \cdot \left(P^{CM}_{n,t} - M_{OP} - M_{SB}\right) - K_{OP\to SB}(\bar{X}) & \text{if } s = OP \text{ and } u = \ SB \\ \frac{1}{2} \cdot \left(P^{CM}_{n,t} - M_{OP} - M_{SB}\right) - K_{SB\to OP}(\bar{X}) & \text{if } s = SB \text{ and } u = \ OP \\ -M_{SB} & \text{if } s = SB \text{ and } u = \ SB \\ -K_{RE}(\bar{X}) - \frac{1}{2}M_{SB} & \text{if } s = SB \text{ and } u = \ RE \end{cases} \tag{3.23}$$

The rest of this section describes the elements of the state variable vector $\bar{X}^{CM}_i$.

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:

$$C_{t,n} = \frac{H_{t,n}}{\bar{H}_{t,n}} \tag{3.24}$$

where $\bar{H}_{t,n}$ is the average heat rate of the competitors of generator n in year t[3].

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

[3] In the following, we use the subscript i to denote a generator-year observation (n, t).

costs of the generators. We have

$$R_t = \begin{cases} 1 & \text{if } t \in [2002, 2003, 2010, 2011, 2012, 2013, 2014] \\ 0 & \text{else} \end{cases} \tag{3.25}$$

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 R_t 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[4] 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:

$$P_t^{NG} = \overline{P^{NG}}_t - \overline{P^{NG}}_{t-1} \tag{3.26}$$

where $\overline{P^{NG}}_t$ 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.

We present the state variable correlation matrix in Table 3.2. If state variables are highly correlated, we can run into issues with multicollinearity in our models. Because of low correlations, we do not expect multicollinearity to be a problem.

From the discussion in Section 2.3.2, where we emphasize the distribution of age for retired plants, one could argue that we should include a variable for the generator age in our model formulation. The effect of older generators becoming less attractive will be captured in the time-varying heat rate in the calculation of C_i, and also in the R_i variable.

[4] Since we have yearly data on decisions, we use a yearly average time series for NG price.

Table 3.2: Correlation between state variables

	C_i	P_i	P_i^{NG}	R_t
C_i	-	-0.196	-0.012	0.004
P_i	-0.196	-	-0.198	0.039
P_i^{NG}	-0.012	-0.198	-	0.144
R_i	0.004	0.039	0.144	-

3.4 Clustering analysis

When including additional exogenous factors in the state process vector, the dimensionality of the problem expands. This is known as the curse of dimensionality, where the number of sampling points required to get statistically significant estimates grow exponentially as the vector space is expanded (Keogh and Mueen, 2017). Computational time will also grow accordingly for discrete dynamic problems. To avoid these problems, we utilize k-means clustering to construct a finite number of observation clusters that minimizes the Euclidean distance from the empirical data to the clusters. This means that optimization is done using a finite number of clusters as allowed values for the state variables, as each empirical observation is assigned to one of k clusters. Figure 3.1 illustrates this approach using three state variables and five clusters for all generator-year observations in our dataset[5]. The small markers represent generator-year observations, and the large markers indicate the cluster centroids. It is clear from Figure 3.1 that each generator-year observation is allocated to the nearest cluster using a measure of Euclidean distance.

3.5 Choice probability counterfactual analysis

Figure 3.2 illustrates how we use the choice probability matrix from the optimization model to do a counterfactual analysis. Given the current operational state and the cluster in which the observation belong, the choice probability matrix is calculated. This matrix contains information about the probability of switching to either of the possible other states, given the state variable vector and the current state. Using this, we

[5]We used 30 clusters and four state variables in our capacity model formulation.

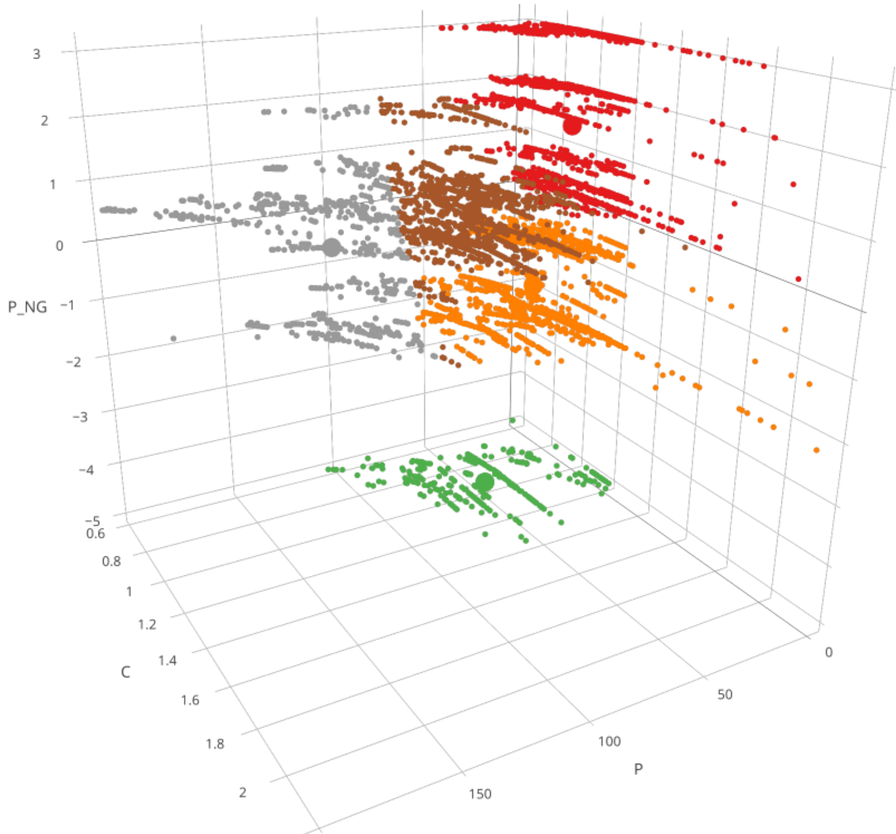


Figure 3.1: Illustration of k-means clustering

conduct a counterfactual analysis on the capacity payments. By adjusting the capacity payment levels, we get new, counterfactual, generator-year observations that we match to the same set of clusters. If we assume that the agent behaves according to the choice probability matrix, we can generate sets of switches under both the original and simulated capacity payment levels, because the generator-year observations will be assigned to different clusters depending on the level of capacity payments. Therefore, the predicted switching behavior will change. The counterfactual sets of switching allow us to study how adjusted capacity payments change the switching behavior.

The switching behavior predicted by the model, when assuming that decision makers act according to the choice probability matrix, deviate substantially from the observed behavior. However, we believe that the model captures the most important market dy-

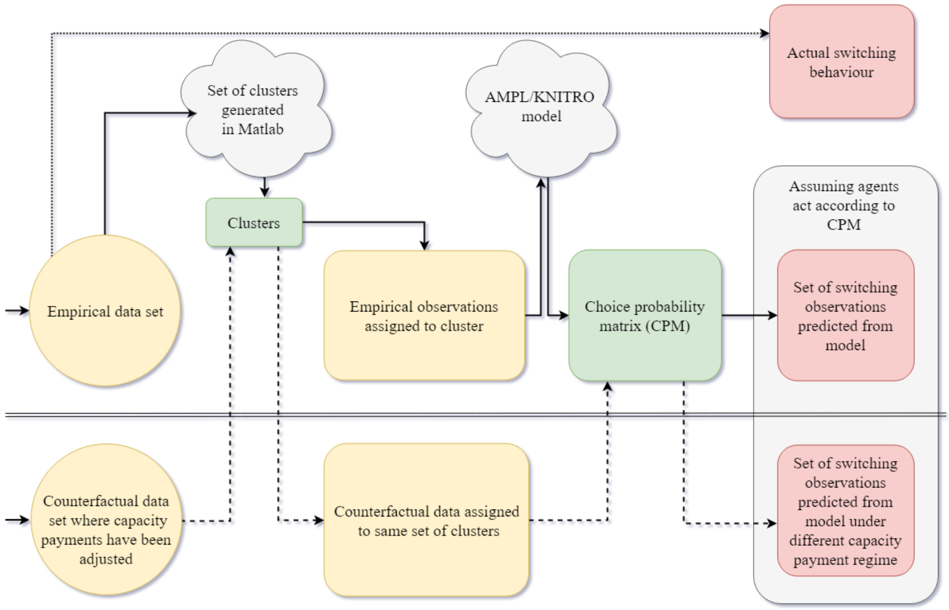


Figure 3.2: Counterfactual model overview

namics. Therefore, by systematically changing the level of capacity payments we can simulate how this will influence switching behavior.

In the counterfactual analysis, we present scenarios with different levels of capacity payments and study the predicted switching behavior under these scenarios. We conduct a sensitivity analysis to assess the responsiveness of the decision makers to changes in the capacity payment level, as predicted by the counterfactual model.

Ideally, a capacity remuneration mechanism should incentivize the right amount of investment in capacity and create an incentive for generators to be available in times of scarcity. Measuring the performance of the RPM is out of the scope of this thesis. We focus on the effect of the capacity payments introduced through RPM on the switching behavior of peaking generators.

Chapter 4

Results and discussion

4.1 Energy-only formulation

Table 4.1 shows the results from the estimation of the energy-only formulation for the period before the introduction of the RPM.

Table 4.1: 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 $K_{SB\to RE}$ 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.

4.2 Capacity market formulation

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 4.2 present the range and average for the state variable vector X_i.

Table 4.2: 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 4.3. Significance levels from parametric bootstrapping are indicated with asterisks in parentheses. For an in-depth interpretation of the results, we refer the reader to Appendix B, where sample splits based on generator age and fuel type are presented in Table B.1 and Table B.2 respectively.

Table 4.3: Capacity market formulation

	Estimated value
M_{OP}	33.565 (***)
M_{SB}	0 (***)
$K_{SB \to OP}$	
Intercept	0
C_i	22.457
P_i^{NG}	2.074 (*)
R_i	-14.281 (***)
$K_{OP \to SB}$	
Intercept	1.233
C_i	-38.628 (**)
P_i^{NG}	-7.435 (***)
R_i	13.049 (***)
$K_{SB \to RE}$	
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

4.2.1 Maintenance cost estimates

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[1].

[1] An example could be exhaust gas treatment processes.

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 $K_{SB\to OP}$ at a moderate level. The results from the energy-only formulation in Table 4.1 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 $K_{SB\to OP}$ as a lump sum. This gives high startup costs, and low or zero SB maintenance costs, as seen in Table 4.3. 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[2].

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.

4.2.2 Switching cost estimates

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, $K_{SB\to OP}$

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

[2]Efforts were made to put restrictions on the maintenance costs to allow only the positive M_{SB} and low $K_{SB\to OP}$ set of solutions, without meaningful results.

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_i^{NG}, 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 differences between fuel types are further treated in Appendix B.

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 $SB \rightarrow OP$ transitions in the years before the introduction of new policy schemes. Looking at Figure 2.1, 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, $K_{OP \to SB}$

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, $K_{SB \to RE}$

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 second-hand 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 NG[3]. 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.

[3]A sample split on fuel type is presented in Appendix B.

Chapter 5

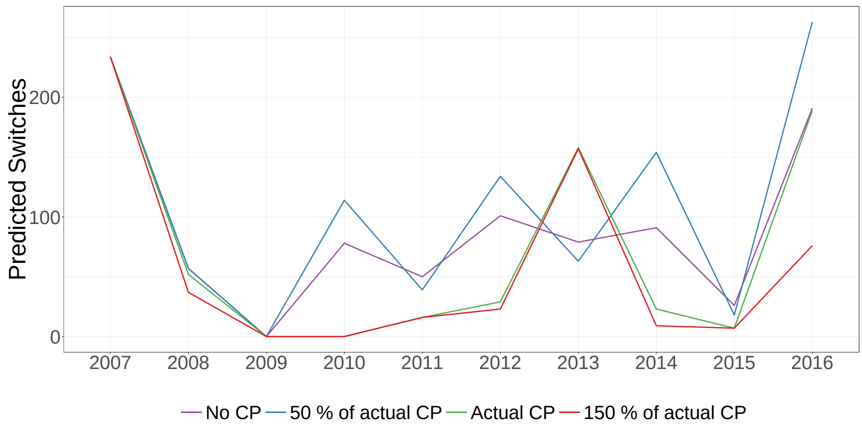
Counterfactual analysis

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.

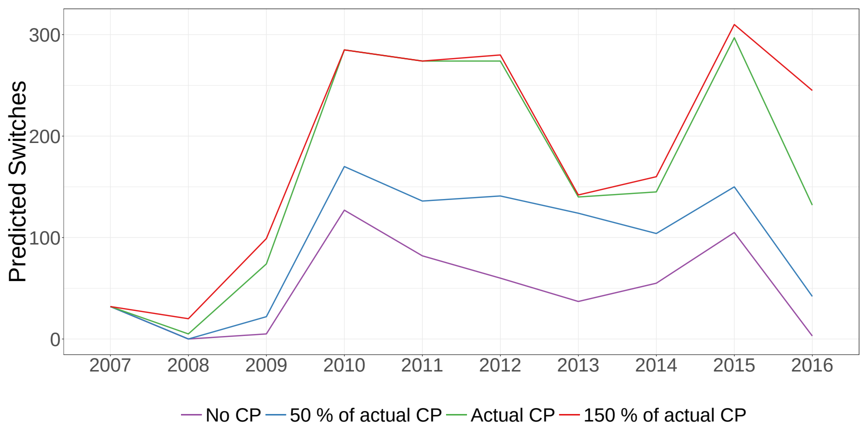
Figure 5.1 shows the switching behavior under different capacity payment (CP) scenarios as predicted by the counterfactual model. The predictions show less switching and more plants staying in *OP* when capacity payments are high. This is in line with the regulator's goal of having generators ready to deliver energy when needed.

For the switching behavior predicted in Figure 5.1a, 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 5.1b.

Figure 5.2 plots the result of a sensitivity analysis on the capacity payment levels in the counterfactual model. Figure 5.2a 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 5.2b 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 5.2c 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 5.2a.

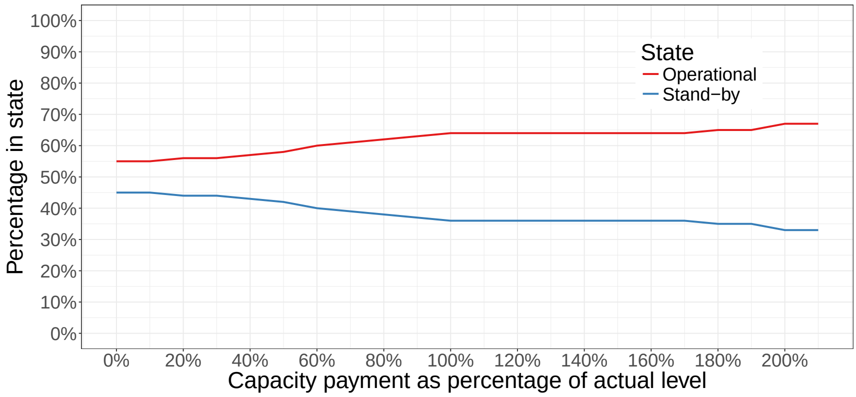


(a) $OP \rightarrow SB$

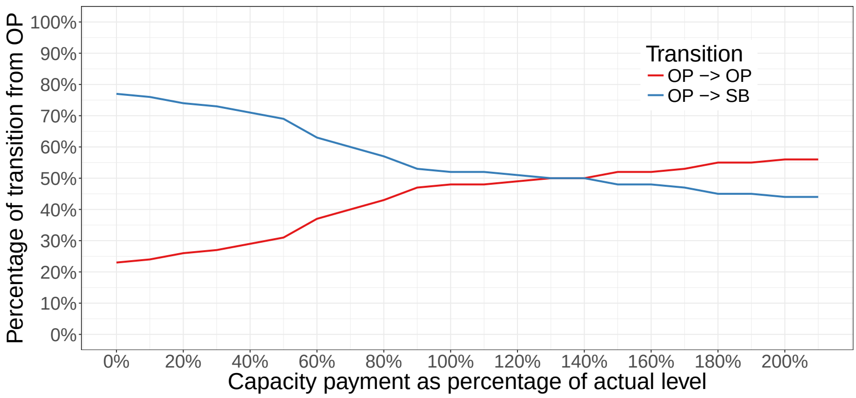


(b) $OP \rightarrow OP$

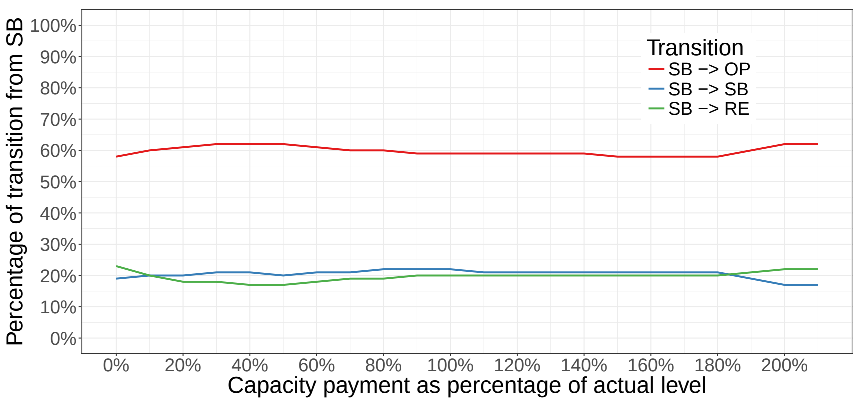
Figure 5.1: Counterfactual analysis on switching behavior from OP



(a) Division between operational states



(b) Transitions from the *OP* state



(c) Transitions from the *SB* state

Figure 5.2: Sensitivity analysis of capacity payments

Chapter 6

Conclusion

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 staying in *OP*.

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.

References

Aguirregabiria, V. and Mira, P. (2007). Sequential Estimation of Dynamic Discrete Games. *Econometrica*, 75(1):1–53.

Aguirregabiria, V., Mira, P., and Roman, H. (2007). An Estimable Dynamic Model of Entry, Exit, and Growth in Oligopoly Retail Markets. *The American Economic Review*, 97(2):449–454.

Bajari, P., Benkard, L. C., and Levin, J. (2007). Estimating Dynamic Models of Imperfect Competition. *Econometrica*, 75(5):1331–1370.

Bhagwat, P. C., Iychettira, K. K., Richstein, J. C., Chappin, E. J., and Vries, L. J. D. (2017). The Effectiveness of Capacity Markets in the Presence of a High Portfolio Share of Renewable Energy Sources. *Utilities Policy*, 48:76 – 91.

Botterud, A., Korpås, M., Vogstad, K., and Wangensteen, I. (2002). A Dynamic Simulation Model for Long-Term Analysis of the Power Market. *Power Systems Computation Conf.*

Cepeda, M. and Finon, D. (2013). How to Correct for Long-Term Externalities of Large-Scale Wind Power Development by a Capacity Mechanism? *Energy Policy*, 61:671 – 685.

Cramton, P. and Stoft, S. (2005). A Capacity Market that Makes Sense. *The Electricity Journal*, 18(7):43 – 54.

Dahlan, N. Y. and Kirschen, D. S. (2014). Generation Investment Evaluation Model in Electricity Market with Capacity Mechanisms. *International Review of Electrical Engineering (IREE)*, 9(4).

Dixit, A. K. and Pindyck, R. S. (1994). *Investment under Uncertainty*. Princeton University Press.

Fleten, S.-E., Haugom, E., Pichler, A., and Ullrich, C. J. (2017). Structural Estimation of Switching Costs for Peaking Power Plants. Working paper, Norwegian University of Science and Technology.

Fleten, S.-E., Johansen, M., Pichler, A., and Ullrich, C. J. (2015). A Structural Estimation Analysis of the Strategic Switching of Peak Generators. In *Proceedings of NHH FIBE 2016*. Available at: `http://conference.nhh.no/fibe/2016/uploads/st734594fl.pdf`, downloaded 18.04.2018.

Hach, D., Chyong, C. K., and Spinler, S. (2016). Capacity Market Design Options: A Dynamic Capacity Investment Model and a GB Case Study. *European Journal of Operational Research*, 249(2):691 – 705.

Hogan, W. W. et al. (2005). On an "Energy Only" Electricity Market Design for Resource Adequacy. Working paper, Harvard University.

Hotz, V. J. and Miller, R. A. (1993). Conditional Choice Probabilities and the Estimation of Dynamic Models. *The Review of Economic Studies*, 60(3):497–529.

Institute of Energy Research (2013). Impact of EPA's Regulatory Assault on Power Plants. Washington: Institute of Energy Research.

Keogh, E. and Mueen, A. (2017). Curse of Dimensionality. In *Encyclopedia of Machine Learning and Data Mining*, pages 314–315. Springer.

Lefebvre, A. H. and Ballal, D. R. (2010). *Gas Turbine Combustion: Alternative Fuels and Emissions*. CRC press.

McFadden, D. et al. (1973). Conditional Logit Analysis of Qualitative Choice Behavior. Published by Institute of Urban and Regional Development, University of California Oakland.

Najjar, Y. S. and Goodger, E. M. (1981). Soot Oxidation in Gas Turbines Using Heavy Fuels. *Fuel*, 60(10):987–990.

Oren, S. (2005). Ensuring Generation Adequacy in Competitive Electricity Markets. *Electricity Deregulation: Choices and Challenges*, pages 388–414.

Ott, A. L. (2012). Evolution of Conventional, Renewable and Alternative Resources in PJM Market Operations. In *Power and Energy Society General Meeting, 2012 IEEE*, pages 1–3.

Pakes, A., Ostrovsky, M., and Berry, S. (2007). Simple Estimators for the Parameters of Discrete Dynamic Games (With Entry/Exit Examples). *The RAND Journal of Economics*, 38(2):373–399.

Pesendorfer, M. and Schmidt-Dengler, P. (2008). Asymptotic Least Squares Estimators for Dynamic Games. *Review of Economic Studies*, 75(3):901–928.

Petitet, M., Finon, D., and Janssen, T. (2017). Capacity Adequacy in Power Markets Facing Energy Transition: A Comparison of Scarcity Pricing and Capacity Mechanism. *Energy Policy*, 103:30 – 46.

Pfeifenberger, J., Newell, S., Spees, K., Hajos, A., and Madjarov, K. (2011). Second Performance Assessment of PJM's Reliability Pricing Model. Prepared for PJM Interconnection, L.L.C.

PJM Interconnection, L.L.C (2018). Explaining Power Plant Retirements in PJM. Available at: `http://learn.pjm.com/three-priorities/planning-for-the-future/explaining-power-plant-retirements.aspx`, accessed: 2018-05-01.

Rust, J. (1987). Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher. *Econometrica*, pages 999–1033.

Rust, J. (1994). Structural Estimation of Markov Decision Processes. *Handbook of Econometrics*, 4:3081–3143.

Stoft, S. (2002). *Power System Economics: Designing Markets for Electricity*. Wiley.

Su, C.-L. and Judd, K. L. (2012). Constrained Optimization Approaches to Estimation of Structural Models. *Econometrica*, 80(5):2213–2230.

Thome, K. E. and Lin Lawell, C.-Y. C. (2015). Investment in Corn-Ethanol Plants in the Midwestern United States. Working paper, University of California at Davis.

United States Department of Energy (2014). Transmission Constraints and Congestion in the Western and Eastern Interconnections, 2009-2012.

U.S. Energy Information Administration (2010). Updated Capital Cost Estimates for Electricity Generation Plants. Office of Energy Analysis.

U.S. Energy Information Administration (2018). Assumptions to the Annual Energy Outlook 2018. Energy Market Module.

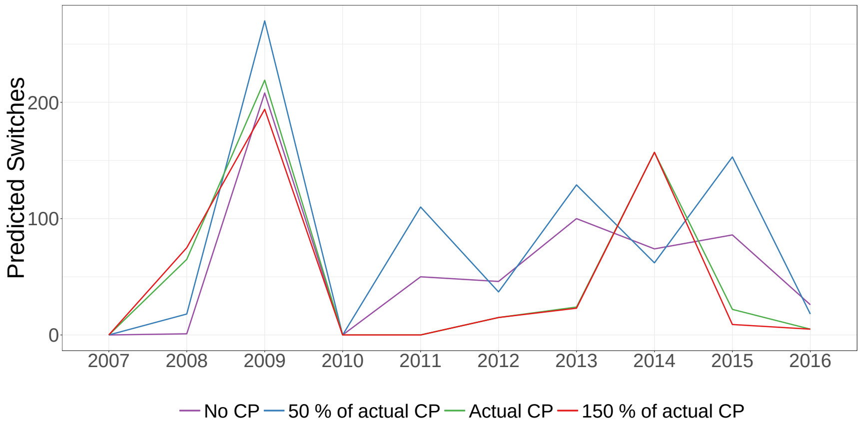
Appendix A

Extended counterfactual analysis

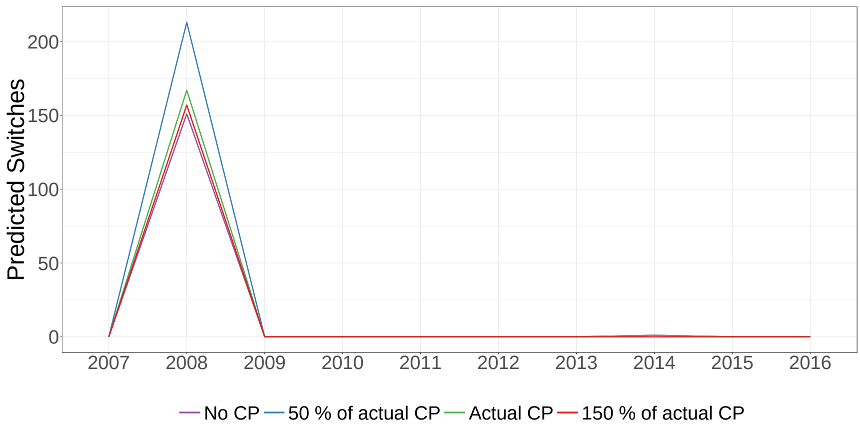
Figure A.1 shows the predicted switching behaviour from the *SB* state under different levels of capacity payments. From Figure A.1a, it is clear that increased capacity payments generally lead to a reduction of switches from *SB* to *OP*. This is caused by the fact that under high capacity payments, the share of generators in *SB* is low, so there are fewer candidates for making this switch. They rather choose to stay in *OP* as seen in Figure 5.1b. This effect becomes clear from looking at Figure 5.2, where the total share of capacity in *OP* state is increasing as capacity payment levels increase.

As Figure A.1c illustrates, there are more retirements when the capacity payments are reduced. This tendency is even more pronounced when capacity payments are removed compared to when they are decreased by 50%. We suspect that some generators follow a strategy in which they clear the capacity auction, but bid high in the electricity auction so that they avoid being dispatched. In effect, they are compensated through the capacity market without actually producing electricity. When pursuing such a strategy, heat rate, emissions and how expensive maintenance is becomes irrelevant, making it an attractive strategy for old generators. However, if capacity payments are absent, the strategy becomes unfeasible, and the old generators would rather retire.

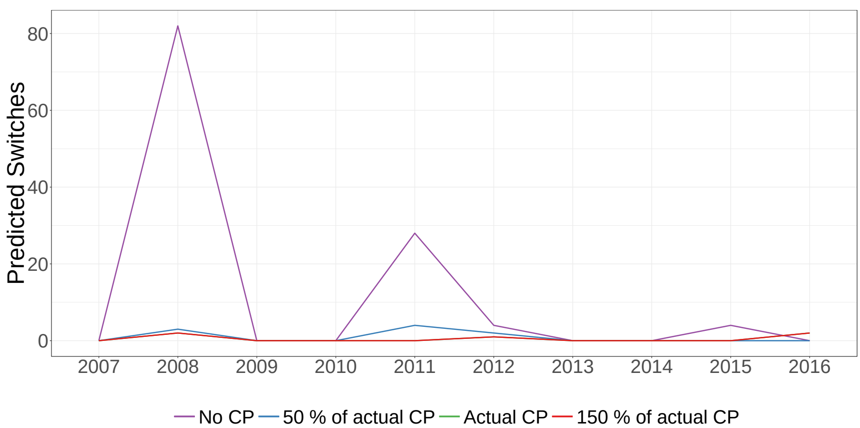
Figure A.1b indicates that no plants choose to stay in the standby state after 2009; those who are in standby switch to either OP or RE the following year.



(a) $SB \to OP$



(b) $SB \to SB$



(c) $SB \to RE$

Figure A.1: Counterfactual analysis on switching behavior from SB

Appendix B

Sample splits for the capacity market formulation

The following sections present the results for sample splits of the dataset. These results serve as an addition to the results presented in Chapter 4, but the reader should be aware of the fact that these results are derived based on an even lower amount of observed switches than presented in Table 2.1. The results should be interpreted with this in mind. We will only comment on the most interesting findings.

Firstly, in Table B.1, we present results for a sample split based on the age of the generators. Secondly, in Table B.2, results for a sample split based on fuel type are presented. For the age split, generators younger than 25 years are compared to those older than 25 years. 25 years is chosen to split the dataset roughly in half, in addition to being close to the average generator age of 22.1 years. This gives 5740 generator-year observations in the youngest group, and 4661 in the group older than 25 years. For the fuel type sample split, we compare units running on natural gas to the units using distillate fuel oil or kerosene[1]. The NG sample split counts 6808 generator-year observations, compared to 3593 for the other fuel types.

[1]DFO and KER fuel prices have a correlation of 0.99.

B.1 Age of generator

Table B.1: Capacity market formulation, stratified by age

	Split by age	
	Below 25 years	Above 25 years
M_{OP}	55.180 (***)	13.365 (***)
M_{SB}	0	0
$K_{SB\rightarrow OP}$		
Intercept	0	0
C_i	130.411 (***)	94.784 (***)
P_i^{NG}	-2.375 (**)	3.765 (**)
R_i	2.506	-5.423
$K_{OP\rightarrow SB}$		
Intercept	0	0
C_i	-173.203 (***)	-96.660 (***)
P_i^{NG}	-15.525 (***)	-10.687 (***)
R_i	18.831 (***)	5.599
$K_{SB\rightarrow RE}$		
Intercept	-23.986	-177.676 (***)
C_i	-123.301 (***)	-10.512
P_i^{NG}	-9.261(*)	-5.316 (***)
R_i	15.973	0.600
Observations	5740	4661
Note:		*p<0.1; **p<0.05; ***p<0.01

Table B.1 shows that the maintenance cost in operation is lower for the older generators, with high significance. In general, we would expect to see the opposite effect; a higher maintenance cost for older units as older equipment need more care. It is possible that the evolution of the peaker role discussed in Chapter 1 play out differently for generators of different ages. Older units that clear the capacity market auction, but rarely are called upon to deliver in the energy market because of high variable cost, will be subject to lower actual wear than younger units which are dispatched more frequently.

For the perceived startup cost, we have highly significant estimates for the coefficients for the inverse competitive advantage. For both age groups, the coefficient is positive and large in magnitude indicating that the perceived cost of starting up a generator with low competitiveness is higher than for more competitive units. The competitiveness of the unit is apparently more important for the younger units.

For the shutdown cost, the C_i coefficient is estimated with the opposite sign as the corresponding startup cost coefficient. Again, the estimated coefficient is larger in magnitude for the younger generators, indicating that the competitiveness is more important among the younger generators. Also for the natural gas price, P_i^{NG}, the perceived shutdown costs decreases more for younger generators than it does for the old when gas prices are increasing.

For the retirement cost, the intercepts are estimated to be negative, with a larger magnitude for older units than for younger units. This is explained by the fact that space and resources occupied by an old, inefficient and highly polluting generator are more valuable for alternative usage than is the case for a cleaner, more efficient and young generator. The intercept is however not significant for the younger units.

B.2 Fuel type

The operational maintenance cost for DFO and KER-fired units is about 40 % higher than the maintenance cost for an NG-fired unit. This difference in maintenance costs can be explained by the more complex combustion system required for the efficient combustion of DFO and kerosene and the higher content of trace elements in heavier fuels (Lefebvre and Ballal, 2010). This leads to more wear on the machinery through more oxidation as well as melting of trace elements such as vanadium. Soot formation is also much more present when DFO is used as fuel than when natural gas is burnt (Najjar and Goodger, 1981).

We estimate that the startup cost increases for less competitive NG generators. This indicates that the NG-fired turbines operate in a highly competitive environment, where entering the operational state is unattractive for less competitive units. Environmental regulations lower the perceived startup costs for natural gas-fired units. This must be viewed in the context of coal baseload retirements as a consequence of regulations.

Table B.2: Capacity market formulation, stratified by fuel type

	Split by fuel	
	NG	DFO and KER
M_{OP}	29.390 (***)	41.992 (***)
M_{SB}	0 (***)	0
$K_{SB \rightarrow OP}$		
Intercept	0.789	1.060
C_i	31.270 (*)	-6.910
P_i^{NG}	1.417	6.378
R_i	-10.563 (**)	9.666
$K_{OP \rightarrow SB}$		
Intercept	7.512	0.768
C_i	-56.618 (**)	6.862
P_i^{NG}	-3.393 (**)	-20.259 (***)
R_i	14.961 (***)	-21.828 (*)
$K_{SB \rightarrow RE}$		
Intercept	-138.036 (***)	-89.744 (**)
C_i	-44.631	-10.644
P_t^{NG}	-4.712 (**)	-9.024
R_i	10.381 (*)	3.282
Observations	6808	3593
Note:	*p<0.1; **p<0.05; ***p<0.01	

The perceived shutdown costs are lower for less competitive natural gas-fired units, indicating fierce competition on heat rates for these generators. We do not see the same effect for the DFO and KER-fired ones.

As expected, the shutdown cost is reduced for NG-fired units when gas prices increase. For the DFO and KER-fired, the shutdown cost lowers drastically with positive changes in the NG price - a somewhat puzzling effect.

Environmental regulations provide a strong signal for NG-fired units to stay operational. For DFO and KER-fired units, we see the opposite effect, however significant only at a 10% level. Since both types of generators compete in the same market, better conditions for cleaner technologies mean higher perceived operational risks for DFO and KER-fired units, and thus a lower perceived cost of shutting down.

For the retirement costs, the lower negative intercept for NG-fired units implies a greater scrapping value for these units. NG-fired units run cleaner, making it easier to comply with new regulations. NG-fired units have also seen a very favorable fuel price development. This increases the second-hand market value for the turbine.

The inverse competitive advantage seems to have no significant impact on the retirement cost. A positive change in the gas price makes it marginally more attractive to retire a natural gas-fired unit. This estimate is significant and makes sense as the market becomes less profitable as the fuel costs increase. The scrapping value decreases for both fuel groups when environmental regulations are introduced. The effect is only significant for NG-fired units, at a 10% level.