Resource Investment in Competitive Markets

Technical Appendix

May 5, 2016

PJM Interconnection

Contents

Appendix A: Supplemental Information for Utility Stock Options Analysis

Methodology for CAPM Analysis:

This analysis estimates a firm's cost of equity capital using the seminal CAPM first developed by Sharpe (1964)[a] and the multifactor models that were formulated later by Fama and French (1995) and Carhart (1997)[b] (the "Fama-French plus Momentum multifactor model") to incorporate effects related to firm size, relative valuation and momentum.[c] The CAPM can be estimated empirically via the following regression model that regresses the returns of a company's stock ($R_{i,t}$) in excess of the risk-free rate ($R_{f,t}$) for a particular set of days (t) on the "excess" returns of the overall U.S. stock market's returns ($R_{m,t} - R_{f,t}$). The regression line produced by the model is called the security characteristic line (SCL), which measures the performance of a security against that of the market portfolio over a period of time. The SCL is plotted on a graph where the y-axis is the excess return of the security over the risk-free rate and the x-access is the excess return of the overall market.

$$SCL \rightarrow R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \varepsilon_{i,t}$$

In the above model, the key components to estimate by regression are the two parameters α_i and $\beta_{I,}$ which are commonly referred to as "alpha" and "beta."[d] The slope of the SCL is the security's beta and the intercept is its alpha. As noted earlier, beta represents the relative riskiness of a firm's stock returns to the overall stock market, and in CAPM theory represents the firm's "systematic" risk, which cannot be diversified away via the holding of a large portfolio of securities. Beta is a pure number and the overall market's beta is set to 1. Thus, for most U.S. stocks the beta is positive and ranges between 0.5 and 2.0.

In contrast to beta, the regression estimate of alpha should be zero on average because, according to the CAPM, a firm should not generate a stock return that is significantly different from the return that it is "required" to earn (i.e., the return the firm should earn based on its beta, the market risk premium, and the risk-free rate). So, firms that possess a positive alpha are providing what economists call a "free lunch" to investors because these firms' stock returns are above what they are required to earn while firms with negative alphas are delivering returns below what they should earn.[e]

In summary, firms that possess a positive alpha are providing stock returns above what they are required to earn while firms with negative alphas are delivering returns below what they should earn.

In equilibrium, all firms should have a zero alpha because investors will drive up the prices of positive alpha stocks (thus lowering their returns) and push down the prices of negative alpha stock (and increasing their returns). Consequently, if some firms have consistently positive alphas over a long period of time, one may conclude that the

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[a] William F. Sharpe (1964) Capital asset prices: a theory of market equilibrium under conditions of risk," Journal of Finance 19, 425-442.

[b] Eugene F. Fama and Kenneth R. French (1995) "Size and Book-to-Market Factors in Earnings and Returns," *Journal of Finance* 50, pp. 131-155; and Mark M. Carhart (1997) "On Persistence in Mutual Fund Performance," *Journal of Finance* 52, 57-82.

[c] To streamline the discussion, PJM focuses on the "simple" CAPM approach, but, where relevant, PJM also describes the results of the Fama-French plus Momentum multi-factor model. As reported below, the results from the more complicated model serve as a robustness check and confirm the simple CAPM results in all material respects.

[d] The variable, $\varepsilon_{t,t}$, is an error term, also referred to as a residual, and, by construction, is zero on average within a regression model.

[e] A negative alpha means that a stock is generating returns *less* than what investors require. In contrast to a positive alpha's "free lunch," a negative alpha is essentially an "overly expensive lunch" from the investors' standpoint.

market is not efficiently pricing these stocks in order to move alpha to zero in due time. This conclusion also holds true for stocks with consistently negative alphas.

To test the above model, PJM ran CAPM regressions on daily return data for each firm in the sample for every year from 2000 to 2015. This approach allows firms to enter and exit the analysis to mitigate potential survivorship bias and thus enables one to average the alphas and betas for both merchant and regulated firms for each year. In addition, it allows the measures of alpha and beta to vary each year as financial markets and economic conditions fluctuate greatly over the 16-year period. PJM estimated 351 sets of alphas and betas for 2000-2015 and then averaged them for the two groups during each year to create 16 annual estimates of alphas and betas for merchant and regulated firms, as shown in the CAPM Results section below. PJM then compared the average values of alpha and beta across these two types of firms for each year in order to examine whether certain firms were riskier than others and whether there were any significantly positive or negative alphas.

The results were the alphas and betas of the CAPM (and for the multifactor Fama-French plus Momentum model as a robustness check) for each of the nine publicly traded merchant firms and 22 regulated firms. Table 1 below provides a complete list of the 31 firms.

Table 1. List of companies used to estimate the CAPM risk measures:

Merchant Firms	
Company Name	**Ticker**
AES Corporation	AES
Calpine Corp.	CPN
Dynegy Inc.	DYN
GenOn Energy Holdings Inc.	GEN
Mirant Corporation	MIR
NRG Energy, Inc.	NRG
Reliant Resources Inc.	RRI
Southern Energy (precursor to MIR)	SOE
Talen Energy Corp	TLN

Regulated Firms	
Company Name	**Ticker**
Ameren Corp	AEE
Cleco Corp New	CNL
Edison International	EDE
Great Plains Energy Inc.	GXP
Idacorp Inc.	IDA
Kansas City Power & Light	KLT
Alliant Energy Corp	LNT
Madison Gas & Electric Co	MDSN
M G E Energy Inc.	MGEE
Minnesota Power Inc.	MPL

Nextera Energy Inc.	NEE
Northern States Power Co MN	NSP
NV Energy Inc.	NVE
O G E Energy Corp	OGE
Otter Tail Power Co	OTTR
Public Service Co NM	PNM
Pinnacle West Capital Corp	PNW
Portland General Electric Co	POR
Scana Corp	SCG
Southern Co	SO
Western Resources Inc.	WR
X C E L Energy Inc.	XEL

Data Sources:

For January 2000 through December 2015, PJM used CRSP daily return data for the underlying merchant and regulated stocks as well as market-wide measures such as the CRSP Value-Weighted Total Return Index's return and other factors such as one-month Treasury-bill rates, as well as Fama-French and Carhart factors related to firm size, relative market valuation and momentum.

Bloomberg's option page (OMON) and other functions were used to retrieve the option-related implied and historical volatilities based on currently traded options on the merchant and regulated firms, as of March 29, 2016.

Options-Related Results:

The below analysis of utility stock options confirms the beta results as described in the main body of the paper.

In addition to the CAPM-related findings, we can examine the total risk, or volatility, of a firm's stock returns using standard deviation as an alternative risk metric. With respect to the options data, the implied and historical volatilities based on March 29, 2016, options for merchant firms range from 2.8 and 3.9 times larger than the volatilities of regulated firms' options. Thus, merchant firms have historically experienced higher stock return volatility and options investors are expecting this volatility to continue into the future, as evidenced by the high implied volatilities reported below. This confirms the earlier beta analysis which showed that merchant firms are perceived as much riskier than regulated firms. See Table 2 below for details.

Table 2. List of Stock Options used to Estimate the Standard Deviations of Annual Returns[f]

Call Option's Maturity & Strike	Ticker	Expiration Date	Open Interest	Implied Volatility % (Mid Price)	Historical Volatility % last 30 Days	Historical Volatility % last 60 Days	Historical Volatility % last 90 Days
CPN US 06/17/16 C14	CPN	6/17/2016	346	42.92	38.8	55.13	52.29
DYN US 06/17/16 C12.5	DYN	6/17/2016	574	71.93	76.83	91.03	90.62
NRG US 06/17/16 C12	NRG	6/17/2016	1,318	59.13	64.05	71.44	81.04
TLN US 07/15/16 C7.5	TLN	7/15/2016	540	63.16	79.28	74.76	71.97
AES US 05/20/16 C11	AES	5/20/2016	5,708	31.45	33.17	39.48	36.3
Merchant Firm's Average			**1,697**	**53.72**	**58.43**	**66.37**	**66.44**
Merchant Firm's Median			**574**	**59.13**	**64.05**	**71.44**	**71.97**
MGEE US 05/20/16 C50	MGEE	5/20/2016	41	24.22	27.02	24.89	22.97
XEL US 06/17/16 C40	XEL	6/17/2016	907	19.76	13.5	15.24	16.23
AEE US 06/17/16 C50	AEE	6/17/2016	666	17.45	17.45	18.2	19.15
GXP US 06/17/16 C30	GXP	6/17/2016	313	22.35	13.74	18.11	18.29
POR US 06/17/16 C40	POR	6/17/2016	106	20.43	18.76	20.77	21.48
LNT US 07/15/16 C72.5	LNT	7/15/2016	10	17.49	13.94	16.36	19.17
CNL US 06/17/16 C55	CNL	6/17/2016	614	1.98	51.77	36.45	30.23
IDA US 05/20/16 C75	IDA	5/20/2016	67	20.28	15.23	16.92	17.28
NEE US 06/17/16 C115	NEE	6/17/2016	2,296	17.43	16.34	17.15	18.45
OGE US 06/17/16 C30	OGE	6/17/2016	115	19.5	28.36	28.31	25.69
OTTR US 07/15/16 C30	OTTR	7/15/2016	135	20.44	16.73	25.71	23.81
PNM US 05/20/16 C35	PNM	5/20/2016	15	22.41	18.51	19.46	18.69
SCG US 05/20/16 C70	SCG	5/20/2016	707	17.39	13.94	16.13	18.08
SO US 05/20/16 C50	SO	5/20/2016	4,588	15.89	14.34	15.65	15.41
WR US 05/20/16 C50	WR	5/20/2016	122	31.55	28.23	25.53	24.01
Regulated Firm's Average			**713**	**19.24**	**20.52**	**20.99**	**20.60**
Regulated Firm's Median			**135**	**19.76**	**16.73**	**18.20**	**19.15**
Ratio of Avg. Merchant / Avg. Regulated (x)				**2.8**	**2.8**	**3.2**	**3.2**
Ratio of Median Merchant / Median Regulated (x)				**3.0**	**3.8**	**3.9**	**3.8**

Source: Bloomberg OMON page accessed March 29, 2016.

Based on the above results and analysis, we can conclude that investors view merchant firms as much riskier than regulated firms, with betas that are 37-65 percent higher and standard deviations that are nearly three-to-four times greater. Thus, one would expect merchant firms to earn a much higher level of return than the firms that are more tightly regulated. However, the opposite seems to be true as the consistently positive alphas for regulated firms indicates these companies are earning returns higher than what they should be expected to earn given their much lower level of risk.

[f] The first column of each row refers to the specific stock option used in the analysis. For example, in the first row of data, it refers to a call option on Calpine stock (CPN) with a strike (or exercise) price of $14 per share with an expiration date of June 17, 2016.

Appendix B: Empirical Analysis of Coal Unit Upgrades and Retirements under MATS

Background

On December 16, 2011, the Environmental Protection Agency issued the final Mercury and Air Toxics Standards (MATS) rule. The final rule requires coal- and oil-fired electric generating units with a capacity of 25 megawatts or greater to meet limits on emissions of mercury, acid gases and nonmetallic hazardous air pollutants[1,2]. Compliance with the standards was required by April 2015. However, the rule ensured that generators needed to maintain grid reliability could obtain a one-year compliance extension from state environmental permitting agencies.

To meet emissions standards, power plants can use a range of pollution control technologies, such as wet and dry scrubbers, dry sorbent injections systems, activated carbon injection systems, fabric filters and electrostatic precipitators. The capital cost of upgrades is typically significant, on the order of tens of millions of dollars. On the other hand, failure to comply with the standards results in civil penalties of $35,000 per violation per day under the Clean Air Act, additional state penalties and exposure to civil liability. Generators needed to decide whether to invest in pollution control technologies, switch fuels or retire.

Retirement decisions are based on the relative economics and regulatory environment of the electricity markets. A unit may retire if higher coal prices, lower wholesale electricity prices (often tied to natural gas prices) or reduced utilization make investment in equipment such as scrubbers uneconomical.

The purpose of the present study was not to estimate the impact of MATS regulation on coal generation overall but to analyze how units respond in the face of rising costs in different regulatory environments.

Natural Experiment

Because the MATS rule is a federal mandate, all coal units that meet the rule's criteria are required to comply. The units are required to comply by a hard deadline, rather than over a period of years, which creates a measureable timeframe for decisions on investment or retirement. MATS differs from other recent environmental policies in that compliance requires more capital investment instead of increased expenses or reduced operations. Moreover, because MATS was issued four years after the implementation of PJM's Reliability Pricing Model Capacity Market, it provides a natural experiment to examine how investment and capital allocation decisions differ between regulated and competitive market paradigms with respect to investment or retirement decisions.

Literature Review

The last half of the 1990s and the first of the 2000s provided a fortuitous natural experiment in which generation facilities operating under both competitive market and cost-recovery paradigms faced identical environmental rules for the control of sulfur dioxide (SO_2) and nitrogen oxide (NOx) emissions. In each case, generators could choose to comply with more expensive, capital-intensive controls or less costly options, such as switching fuels or participating in the associated emissions trading markets.

An array of independent analyses show that regulated utilities made less cost-effective compliance decisions in response to the rules, e.g. Bohi and Burtraw (1992), Fullerton, McDermott and Caulkins (1997), Ariumra (2002), Sotkiewicz (2003), and Sotkiewicz and Holt (2005).

Both Ariumra (2002) and Fowlie (2010) specify logistic regression models to estimate the effect of traditional regulation. Fowlie finds that generation resources in competitive states were less likely to adopt capital-intensive compliance options than regulated facilities or those that are owned/operated by public power

Hypothesis

The natural experiment of MATS allows comparison of capital investment decisions by coal unit owners in regulated cost-recovery environments relative to those in competitive markets. The hypothesis is that PJM's competitive markets will drive economically efficient outcomes more often than regulated environments. Put another way: justifiable investments in upgrades (e.g., meeting an economic threshold cost) are hypothesized to be more likely in PJM and unjustifiable investments less likely in PJM.

Regression Model for Testing Hypothesis

The hypothesis is tested with a population-averaged logistic regression in which the decision to announce retirement is modeled for coal-fired generation units. The retirement decision is measured by observing actual plant retirements, or, in some cases, published announcements of future retirements. A panel data set is used for the estimation period of 2011 to 2013 using the following theoretical model:

$$\Pr(Retirement_{it}) = \frac{1}{1 + \exp\left[-\left(\beta_0 + \sum_{j=1}^{J} \beta_{1j} X_{itj} + \beta_2 t + \sum_{k=1}^{K} \beta_{3k} Z_{ikt} + \sum_{m=1}^{M} \beta_{4m} G_{im}\right)\right]}$$

Where:

- β_0 is the intercept
- β_1 is the estimated independent variable coefficient in which *J* is the number of included variables
- X_{it} is the independent variable *j* for each generator *i* at time *t*
- β_2 is the estimated coefficient of time
- *t* is time
- β_{3k} is the estimated coefficient of time-dependent covariate *k*
- *K* is the number of time-dependent covariates
- Z_{ikt} is the time-dependent covariate *k* of generator *i* at time *t*
- β_{4m} is the regression coefficient of time-independent covariate *m*
- *M* is the number of time-independent covariates
- G_{im} is the time-independent covariate *m* of generator *i*.

The following independent variables were included in the model and are discussed in depth in the following sections:

- PJM
- Age
- Age*PJM
- Size
- Capacity factor
- Estimated MATS associated upgrade costs (EnvUpgradeCosts)
- EnvUpgradeCosts*PJM

Variables and Data Collection

Retirements

The decision to retire was analyzed for a total dataset of 703 coal-fired generating units located within the continental United States. Data on the year of an actual (or in some cases announced) retirement or fuel switching was gathered from several sources, including SNL, EIA and press releases. A fuel switch that precludes coal firing was considered a retirement. Any retirement between 2011 and 2016 was counted as taking place during the relevant MATS period. Actual retirements were treated the same as announced retirement for any year within the MATS period. All units with a 2016 retirement and some units with a 2015 retirement were announcements rather than ex post facto retirement.

Although the final MATS rule was finalized in December 2011, the outlines of the coming rule were clear by the end of 2010[9]. Therefore, units that retired in the year 2011 (but not before) are considered to have done so in anticipation of MATS. Additionally, while MATS required that generators comply by April 2015, it allowed for states to permit conditional extensions into 2016 if the plant was considered critical to grid reliability. Reliability extensions accounted for 18.8 percent of the retirements, while almost 41 percent of retirements were in 2015. This pattern is consistent with findings from the EIA Annual Energy Outlook 2014 in which MATS-associated retirements peak in 2015 but persist into 2016.[3]

Regulatory Environment

In some areas with competitive markets for electric energy, entry and exit of generation units does not take place due to market signals. Rather, new entry is due to decisions by a regulated utility that will be supported by cost recovery from the rate base. For the purposes of capital investment, these areas are effectively regulated monopolies, rather than competitive markets.

In other competitive market areas, price signals do exist for entry and exit in the form of a capacity market similar to that in PJM. However, the capacity market price signal can vary in importance. Consider a market area in which most new generation is not driven by a capacity price. This may be because new generation units, built by regulated utilities, enjoy cost recovery regardless of capacity revenue. In this case, the capacity price may not support new entry on its own. Such a market area may not enjoy the characteristics of a competitive market with respect to capital investment. These areas, too, are effectively regulated monopolies, rather than competitive markets, for the purposes of capital investment.

For most, if not all, generation investors in PJM, capacity market revenue is a significant part of the decision to invest. This applies both to new units and to significant capital upgrades such as those required for MATS compliance.

Finally, consider a regulated utility that builds generation, subject to cost recovery, in a competitive market with a strong capacity price. The capacity price provides a clear signal of the market cost of an additional unit of new generation capacity that is hard for regulators and utilities to ignore. In this case, the competitive market price drives efficient outcomes in new entry and exit even for regulated utilities that enjoy cost recovery for generation.

For this study, generation units were partitioned into two groups, PJM and regulated, according to these criteria:

- Units located within the PJM footprint per the EIA were defined as PJM. This group represents approximately one quarter of the sample,
- Generators located outside of PJM's footprint and within a regulated state in which investment costs were recovered through regulated rates were characterized as regulated.

Table 3 below shows states for which any part was included in the definition. Some states (e.g., Indiana), appear in both categories. Such states are regulated states that are partially in PJM. Units within such states that are in the

[9] Oct. 22, 2009 EPA signed a consent decree (attached) to propose a Maximum Available Control Technology rule for coal and oil units by March 2011, and finalize by Nov. 2011. EPA published an Information Collection Request in Dec 2009 and released the data in Nov 2010. An industry brief from M.J. Bradley & Associates dated January 12, 2011 used this information to calculate expected emissions limits from the imminent rule.

PJM footprint are marked as 'PJM' units. Those outside the PJM footprint are marked as "Regulated" if they meet the above criteria.

Table 3. States Represented in "PJM" and "Regulated" Coal Unit Populations

PJM		***Regulated, non-PJM***		
DE	TN	AL	LA	NV
IL	VA	AR	MI	OK
IN	WV	AZ	MN	SC
KY		CO	MO	SD
MD		FL	MT	TN
MI		GA	NC	UT
NC		IA	ND	WA
NJ		IN	NE	WI
OH		KS	NH	WY
PA		KY	NM	

PJM expanded during the observation period to integrate American Transmission Systems, Inc. and Cleveland Public Power (2011) and East Kentucky Power Cooperative (2013). EKPC has three coal-fired power plants with 10 units. This compares to approximately 176 coal units studied in all of PJM. EKPC had been a PJM member and market participant since 2005, and first studied integration to PJM in 2011. All EKPC units were fully integrated into PJM markets and operations for MATS compliance deadlines in both 2015 and 2016.

All units in the 2015 PJM footprint are considered PJM units for this study.

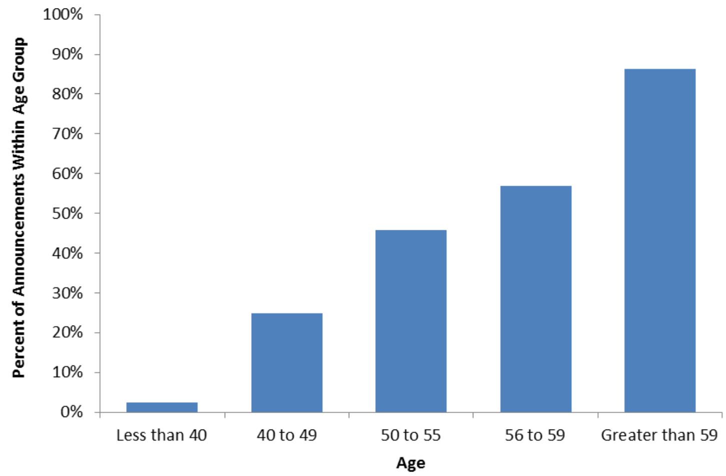
There is not an a priori expectation of the outcome of this variable alone. Note the hypothesis is testing in the interaction of this variable and the environmental upgrade cost variable, as described below.

Age

Age of the unit was calculated as 2015 minus in-service date. In-service dates were collected from the EPA's Air Markets Program database. This database aggregates operational and environmental data for any unit subject to at least one regulation under the Clean Air Act and was extracted in December 2015.

The average age for generators in this analysis was 43 years. Generators that retired tended to be older, with an average age of 53, while generators that remained in operation tended to be younger by approximately 14 years. Figure 1 below displays retirement by age group. Older groups tend to have a higher percentage of units that retire.

Figure 1. Coal Retirement by Age: United States (2011-2016)

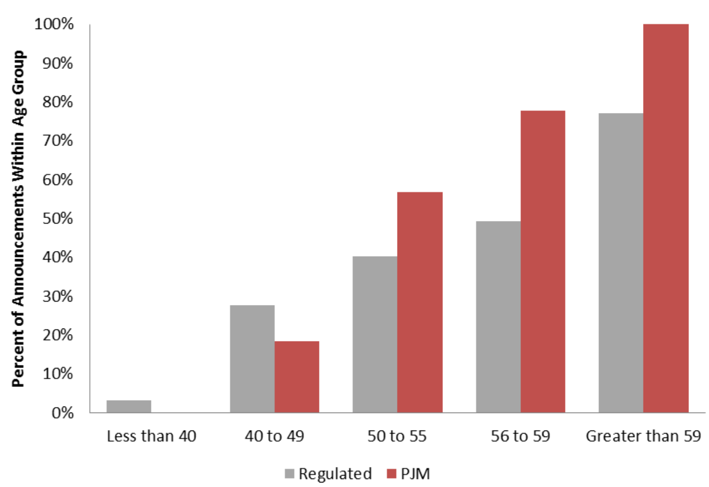


This difference in age between generators that retire versus those that remain in operation may be the result of several factors. In general, older units tend to have relatively higher emissions rates, are less efficient, have higher operating costs, and a higher frequency of both forced and unforced outages. As a result, as generators increase in age, it is expected that the probability of announcing retirement increases.

Age*PJM

The interaction of the PJM variable and the age variable shows contrast in the way that PJM units respond to increasing age relative to the way that regulated units do. It is expected that PJM is more sensitive to increases in age beyond the mean age. This increased relative responsiveness is demonstrated in Figure 2 below in which generators located within PJM tend to have higher shares of retirement as the age moves further away from the average age of 43 years.

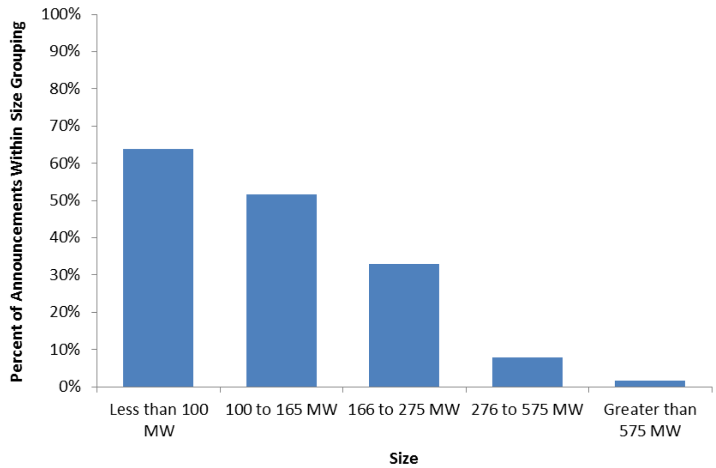
Figure 2. Coal Retirement by Age: PJM versus Regulated Areas, (2011-2016)



Size

Size, measured in MW, was collected from the EIA. Due to economies of scale and other factors, smaller units are expected to be more likely to retire. Figure 3 below demonstrates that larger units tend to have a lower percentage of retirements.

Figure 3. Coal Retirement by Nameplate Capacity: United States (2011-2016)

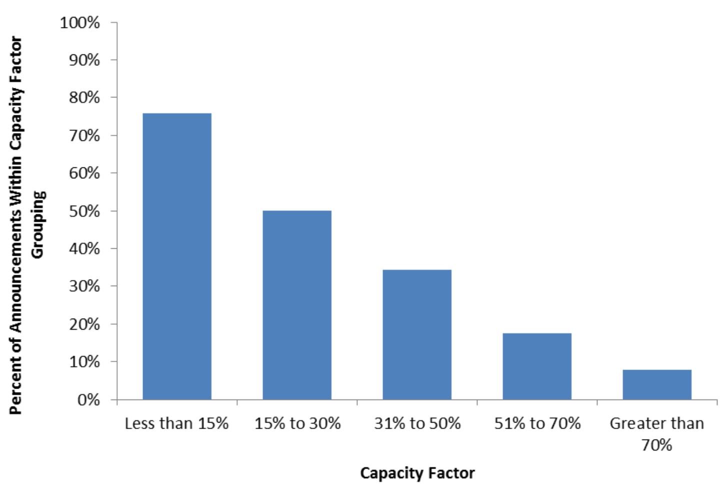


Capacity Factor

Capacity factor data was collected from the EPA's Air Markets Program database. It is the ratio of a unit's actual output to its maximum possible output over one year. The average capacity factor for generators that retired was 35 percent. This is low compared to the average 60 percent capacity factor for generators that remained in operation.

A priori, it is expected that as capacity factor increases, the probability of retirement decreases. This is consistent with the data shown in Figure 4 below, which displays the percentage of generators retiring by capacity factor:

Figure 4. Coal Retirement by Capacity Factor: United States (2011-2016)



Environmental Upgrade Costs

The cost of upgrades to comply with MATS is a key indicator in this study, since high upgrade cost is the primary driver of retirements during this period. Upgrade costs were modeled as described below.

Environmental technology cost calculations by Sargent and Lundy, from the EPA Integrated Planning Model, were adapted in order to model the capital and operating costs of environmental upgrades required to comply with the MATS rule. The necessary operational data on all coal units in the United States were collected from EPA and SNL and modeled the upgrade costs for each unit. The environmental upgrade cost model calculates the capital investment as well as increased variable and fixed operating costs for the predicted retrofits required to meet MATS.

The model chooses among various pollution control technologies depending on the magnitude of historical emissions of pollutants like SO_2 and NOx. All upgrade costs, including capital expenditures with a 20-year life, are converted into a $/MW-day figure for easy comparison.

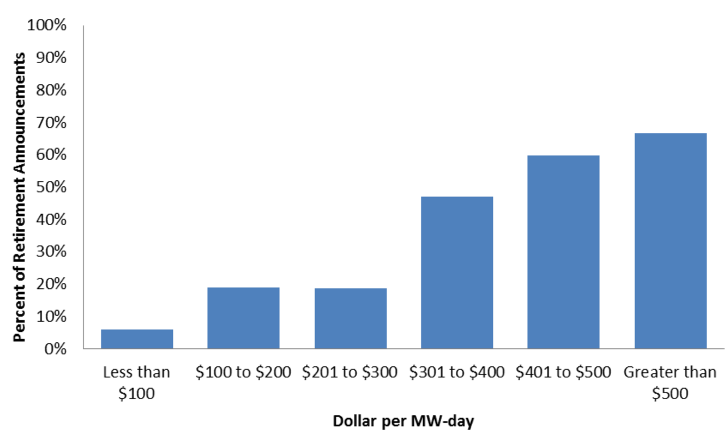
PJM used a similar information and cost model framework in its 2011 study of MATS. It would have been the best information available to generation owners during the period of time when they were making a decision on how to respond to MATS.

A single environmental upgrade cost was used for each unit. Where possible, the cost was modeled based on emissions data from 2011. Units that either retired or upgraded in 2011 were considered to have responded to MATS. However, because 2011 represents an incomplete record of pre-MATS emissions, emissions data from 2010 was used for such units. Units that retired prior to 2011 were excluded from the analysis. Units that upgraded prior to 2011 were considered to have upgraded for reasons not related to MATS.

Some units were already compliant with MATS at the beginning of the observation period, and so have a modeled cost of zero. For plants that were not already compliant with MATS, an observed non-retirement was taken to imply an upgrade and confirmed where possible by observations of actual upgrade investments.

A priori, it is expected that as environmental upgrade costs rise, the probability of retirement rises. Figure 5 below demonstrates such a trend.

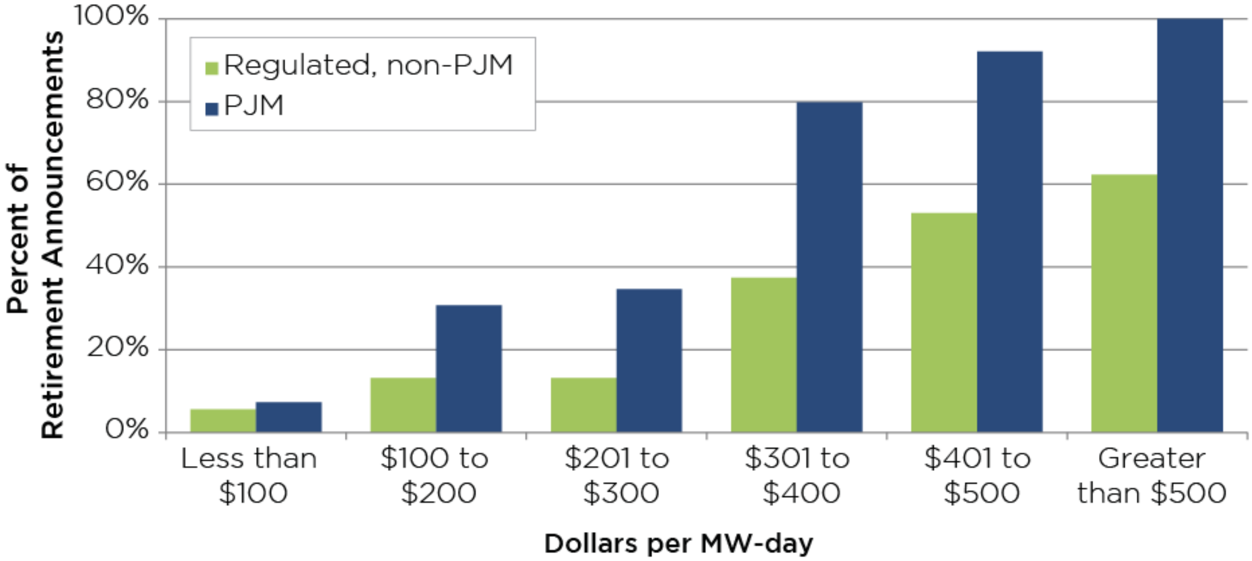
Figure 5. Coal Retirement by Environmental Upgrade Cost: United States (2011-2016)



Environmental Upgrade Costs*PJM

To test the hypothesis that PJM units are more sensitive to higher upgrade costs, the interaction of the "PJM" variable with the "Environmental Upgrade Cost" variable was modeled. Figure 6 below compares PJM and regulated areas with respect to unit retirements at different levels of MATS upgrade costs. Considering that the average estimated upgrade cost is approximated $230 per MW-day, it appears that PJM is more responsive to increasing costs. This becomes particularly pronounced for units as the cost increases surpass the average.

Figure 6. Coal Retirement by Environmental Upgrade Cost: PJM versus Regulated Areas, (2011-2016)



Variables Tested but Not Included

The following variables were tested and found to be insignificant during the observation period:

- Average natural gas prices
- Unit-specific coal prices
- Non-fuel operations and maintenance cost
- Heat rate

Table 4 displays the all descriptive statistics by year, regulatory environment and retirement announcement status:

Table 4. Descriptive Statistics

	2011				2012				2013			
	Announced Retirement		**Remained in Operation**		**Announced Retirement**		**Remained in Operation**		**Announced Retirement**		**Remained in Operation**	
	PJM	*Regulated*	*PJM*	*Regulated*	*PJM*	*Regulated*	*PJM*	*Regulated*	*PJM*	*Regulated*	*PJM*	*Regulated*
Age												
N	76	125	100	392	73	118	98	394	40	94	96	395
Range	41.00 - 64.00	39.00 - 62.00	1.00 - 59.00	0.00 - 62.00	42.00 - 65.00	32.00 - 63.00	2.00 - 58.00	0.00 - 61.00	42.00 - 63.00	33.00 - 64.00	3.00 - 58.00	1.00 - 62.00
Mean +/- Standard Deviation	55.16 +/- 4.84	52.78 +/- 6.02	41.66 +/- 10.22	37.77 +/- 12.86	55.85 +/- 5.15	53.13 +/- 6.44	42.31 +/- 10.01	38.45 +/- 13.15	55.18 +/- 5.85	53.94 +/- 6.65	43.10 +/- 9.98	39.42 +/- 13.04
Capacity Factor												
N	76	125	100	392	73	118	98	394	40	94	96	395
Range	0.01 - 0.90	0.01 - 0.88	0.13 - 0.93	0.01 - 0.97	<0.01 - 0.76	<0.01 - 0.85	0.04 - 0.88	0.02 - 0.99	0.04 - 0.85	<0.01 - 0.81	0.03 - 0.88	0.01 - 0.99
Mean +/- Standard Deviation	0.27 +/- 0.22	0.41 +/- 0.20	0.56 +/- 0.21	0.63 +/- 0.18	0.19 +/- 0.17	0.30 +/- 0.24	0.47 +/- 0.21	0.56 +/- 0.21	0.26 +/- 0.19	0.36 +/- 0.25	0.54 +/- 0.23	0.59 +/- 0.22
Size												
N	76	125	100	392	73	118	98	394	40	94	96	395
Range	34.50 - 615.20	27.00 - 575.00	50.60 - 1425.60	37.50 - 1300	34.50 - 615.20	27.00 - 575.00	50.60 - 1425.60	37.50 - 1300.00	46.00 - 615.20	29.30 - 575.00	50.60 - 1425.60	37.50 – 1300
Mean +/- Standard	174.18 +/-	147.83 +/- 108.02	552.41 +/- 328.69	402.70 +/- 256.40	174.76 +/-	157.49 +/- 117.32	561.53 +/-	405.40 +/- 256.62	230.40 +/-	152.54 +/- 117.27	570.61 +/-	408.05 +/- 256.88

Deviation	101.70				105.00		325.67		141.17		322.74	
Total Estimated Environmental Upgrade Costs												
N	76	125	100	390	73	115	98	390	40	91	96	391
Range	44.50 - 745.40	60.57 - 765.29	0.00 - 411.87	0.00 - 584.24	44.50 - 847.97	60.57 - 765.29	0.00 - 382.09	0.00 - 584.24	44.50 - 847.97	60.57 - 753.50	0.00 - 382.09	0.00 - 584.24
Mean +/- Standard Deviation	315.57 +/- 124.34	377.37 +/- 143.71	134.18 +/- 115.53	195.15 +/- 148.13	331.76 +/- 133.51	372.20 +/- 144.08	128.54 +/- 109.63	194.47 +/- 148.32	315.36 +/- 129.37	369.65 +/- 147.40	130.69 +/- 109.73	194.70 +/- 147.65

Method

Estimation Technique

This analysis used a panel dataset collected for the years 2010 to 2013 to estimate the probability of coal-fired units announcing retirement. Panel models relate cross-sections over time, thus measuring the impact of differences in both time-variant and invariant effects. In allowing for variation across space and time, panel models result in a more efficient and robust estimation technique relative to cross-sectional or time series alone. An advantage of this increased information is that it lessens problems of multicollinearity[4]. The primary benefit of panel models, however, is that they correct for unobserved heterogeneity and mitigate bias due to omitted variables.

Each generator has fundamental attributes that are different from one another, such as quality of management, local political influences or varying tolerance to risk. If these traits influence behavior, then they are considered omitted variables and bias the estimated coefficients. In collecting repeated outcomes for the same set of generators over time, the many factors that are related to retirement decisions are effectively held constant within plants. Thus, this method implicitly controls for influential, idiosyncratic characteristics.[5]

Although the repeated measures approach alleviates within-subject omitted variable bias, it does not come without statistical complications. Observations of the dependent variable within generators may no longer be considered independent nor may it be reasonable to assume that the errors are independent and identically distributed.[6] While the error is assumed stochastic across units, within-subject retirement decisions across the estimation period may be highly correlated. For instance, generators that opt not to retire in 2012 have a higher probability of not retiring in 2013. This within-subject dependence is known as correlated outcomes and must be accounted for to obtain proper estimates of variability used in statistical inference.

To correct for within-subject dependence in models of non-Gaussian distributions, Liang and Zeger introduced generalized estimating equations (GEEs) in their seminal 1986 paper.[7] Known as population-averaged, or marginal models, this estimation technique extends traditional linear models through a nonlinear link function. Conclusions about the population mean are made by relating the average outcome at each occasion to the included covariates in which the expected probability at any given time is a function of the covariates and their average response observed at that time.[8,9] The resulting estimated coefficients describe differences in the average response of observations for which all other covariates are identical.[4] For example, interpretation of the regulatory environment coefficient compares the predicted odds of retirement for the hypothetical average generator located in PJM to the predicted odds for the hypothetical average generator located within a regulated area.

GEEs iteratively solve a system of equations based on quasi-likelihood distributional assumptions. Full distributional assumptions are not necessary for this estimation technique. Instead, marginal models only require specification of the first two statistical moments. Both the mean and variance are conditioned upon the covariates, in which the variance structure is specified through a link function and is dependent upon the population mean. To account for within-subject correlation, a working correlation structure which contains a “best guess” of the within-subject correlation pattern is specified. The choice of correlation pattern is often unclear a priori. However the four most common matrices are as follows:

1. Independent: Repeated observations are uncorrelated.

$$Corr(Y_{ij}, Y_{ik}) = \begin{cases} 1 & j = k \\ 0 & j \neq k \end{cases} \qquad \text{Ex. } \boldsymbol{R}_i|n_i = 4: \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

2. Unstructured: Correlations within any two responses are unknown and must be estimated.

$$Corr(Y_{ij}, Y_{ik}) = \begin{cases} 1 & j = k \\ \alpha_{jk} & j \neq k \end{cases} \qquad \text{Ex. } \boldsymbol{R}_i|n_i = 4: \begin{bmatrix} 1 & \propto_{12} & \propto_{13} & \propto_{14} \\ \propto_{12} & 1 & \propto_{23} & \propto_{24} \\ \propto_{13} & \propto_{23} & 1 & \propto_{12} \\ \propto_{14} & \propto_{24} & \propto_{34} & 1 \end{bmatrix}$$

3. Autoregressive of first order: Equal correlation for given time lag k.

$$Corr\left(Y_{ij}, Y_{ij+1}\right) = \propto^k \ for \ t = 0, \ldots, n_{i-j} \qquad \text{Ex. } \boldsymbol{R}_i|n_i = 4: \begin{bmatrix} 1 & \propto & \propto^2 & \propto^3 \\ \propto & 1 & \propto & \propto^2 \\ \propto^2 & \propto & 1 & \propto \\ \propto^3 & \propto^2 & \propto & 1 \end{bmatrix}$$

4. Exchangeable: Correlation between any two responses of the i^{th} individual is the same.

$$Corr(Y_{ij}, Y_{ik}) = \begin{cases} 1 & j = k \\ 0 & j \neq k \end{cases} \qquad \text{Ex. } \boldsymbol{R}_i|n_i = 4: \begin{bmatrix} 1 & \propto & \propto & \propto \\ \propto & 1 & \propto & \propto \\ \propto & \propto & 1 & \propto \\ \propto & \propto & \propto & 1 \end{bmatrix}$$

Where $\mathbf{R}_i[\alpha]$ is a working correlation matrix with a vector of unknown parameters.[10]

The GEE method uses the specified working correlation structure to compute an initial, "naïve" model estimate through the specified link function. The residuals and model-based estimated within-subject dependencies, $\hat{\alpha}$, are then used to re-estimate coefficients and empirical standard errors. This procedure is iterated until convergence and results in consistent, robust estimates of the regression parameters and their variances.[7]

Model Specification

Link Function

Marginal models allow for the probability distribution to be a member of various exponential distributions through nonlinear link functions. Selection of the appropriate link function is dependent upon type of data and assumed distribution of the outcome variable. For this analysis, the outcome was framed as a dichotomous phenomenon: a generator either did or did not announce retirement. When modeling for such binary outcomes, it is common practice to use a logistic or probit model. The choice between the two is mostly subjective in nature. In practice, results from the two models tend to lead to nearly identical conclusions.[11] For GEEs, logistic link functions are ubiquitous throughout the literature and were therefore selected as the link function for this study.

Working Correlation Matrix

For balanced panels, the choice for the working correlation is flexible because the GEE method is resilient to misspecification of working correlation patterns. Because the empirical standard errors reflect sample dependence, incorrect guesses of the within-subject dependence leads to little efficiency loss.[7] Assuming that the chosen link function and included covariates truly describe how the average expected response relates to the explanatory variables, GEE model parameter estimators converge in probability to the true parameters.[12]

However, the panel in this analysis is unbalanced. Since some generators retired during the estimation period, not all units have an equal number of observations. While GEEs allow for unbalanced panel designs, only the independent working correlation structure may be used, although standard errors for these panels tend to be larger due to loss of efficiency.[13,14,15] But such estimators can have surprisingly good efficiency when the actual correlation is weak-to-moderate.[7] A sensitivity in which the sample is restricted to generators that remain in operation during the entire estimation period was conducted and is discussed further in the sensitivities section.

Overdispersion

Overdispersion occurs when binary data exhibits variances that are larger than assumed under the specified distribution. Although the parameter estimates are not affected, this unanticipated additional variance impacts hypothesis testing. Since the population standard deviation is greater than expected for overdispersed data, standard errors are underestimated and t-statistics become inflated. The risk of Type I error increases as erroneous inferences are more likely to occur because insignificant relationships appear significant.[16]

To test for overdispersion the following dispersion factor was estimated using the approach recommended by McCullagh and Nelder (1989)[17]:

$$\widehat{\sigma^2} = \frac{\chi^2}{(N-K)}$$

where χ^2 is the Pearson goodness-of-fit statistic divided by the degrees of freedom. A $\widehat{\sigma^2}$ greater than one suggests overdispersion. Likewise, a $\widehat{\sigma^2}$ less than one is indicative of underdispersion. The data was tested for overdispersion, in which an estimated dispersion factor greater than one was obtained. To correct for additional variation, the covariance matrix and log likelihoods were scaled.

Outliers

To identify influential outliers the Cook's distance (D_i) statistic was used. Observations with a D_i greater or equal to $4/_N$ were considered potential influential outliers. These observations were ranked in descending order by their estimated D_i and eliminated on an individual, incremental basis. A new D_i was estimated after each elimination cycle, and the observations were re-sorted into descending order. This identification and elimination process was repeated until the overall fit improved but general conclusions remained unchanged. Eight outlier units were removed as a result of this process.

Variable Selection

After adjusting for overdispersion, various linear combinations of variables were tested for significance. Following the method set forth by Milliken and Johnson (1984), variable selection was determined through an iterative constrained optimization process.[18] The first linear combination included all considered variables. This combination was then constrained to equal zero, and maximum likelihood estimates were computed. Likelihood ratio statistics were then computed for each variable. The variable with the least significant likelihood ratio was eliminated and the process was repeated with the new combination. Table 5 below contains each test and the associated p-values.

Table 5. Variable Selection P-Values

Variable	Iteration I	Iteration II	Iteration III	Iteration IV	Iteration IV
PJM	<0.0001	<0.0001	0.0005	0.0003	<0.0001
PJM*Age	<0.0001	<0.0001	0.0049	0.0027	0.0004
Age	0.0396	0.0363	0.0004	0.0015	0.0010
Size	0.0523	0.0339	<0.0001	<0.0001	<0.0001
Capacity Factor	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
EnviroCosts	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
PJM*EnviroCosts	0.0526	0.0484	0.0447	0.0354	0.0296
Fuel Ratio *(Coal $MW-hr/Natural Gas $MW-hr)*	0.1298	0.1282	0.1134	0.1127	-
Heat Rate	0.3872	0.3726	0.3604	-	-
Non-fuel Fix O&M Costs	0.4183	0.4166	-	-	-
Non-fuel Variable O&M cost	0.9041	-	-	-	-

Estimation Results

Table 6 below displays the estimated odds ratios. Under this specification, all the included variables are statistically significant and the model correctly estimates retirement decisions 84 percent of the time.

Estimated Odds Ratios

Table 6. Odds Ratios for Coal-fired Power Plants Announcing Retirement

Parameter	Description	Odds Ratio	Odds Ratio Confidence Interval	
Intercept		0.005**	0.002	0.016
PJM	Located within PJM footprint	0.078**	0.009	0.682
Age	Year - Unit In Service Year	1.052**	1.007	1.098
Age*PJM	Interaction variable	1.097**	1.079	1.115
Size	MW	0.999**	0.998	0.999
CapFac	%	0.057**	0.032	0.103
EnviroCosts	20 Yr Capital Recovery, $MW-day	1.005**	1.005	1.006
EnviroCosts*PJM	Interaction variable	1.003**	1.001	1.005

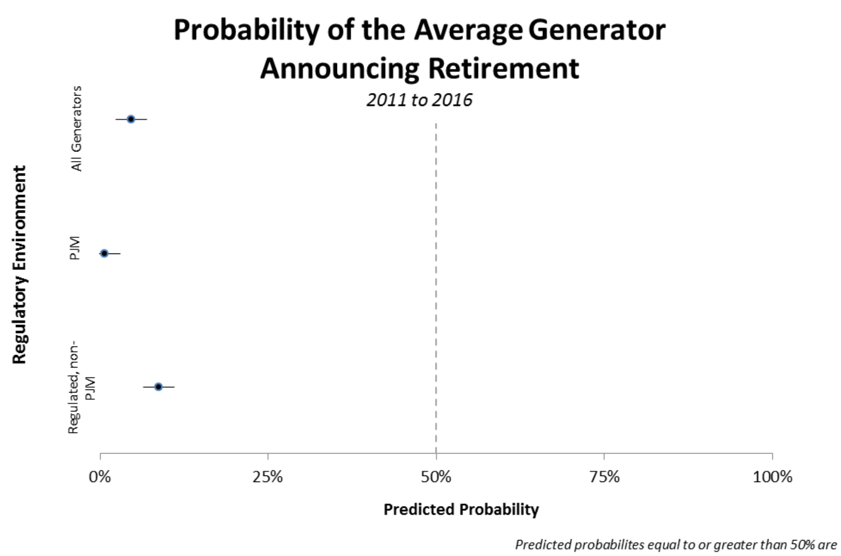
***significant at a 5% level*

N =2,682 **QIC**= 450.28

Percent correctly estimated: 84.15% **QICu** = 462.68

The model estimates that the hypothetical average generator, with average values for all its characteristics, is 12.8 times less likely to retire when located in PJM, relative to the same average generator located within a regulated area. This odds-ratio corresponds with low predicted probabilities of the average generator retiring, regardless of regulatory environment. Since the average generator is a hypothetical generator that is of average age, size, capacity factor and upgrade costs, it is intuitive that the generator would not be predicted to retire, as they are not at risk. Figure 7 below demonstrates that, while the average generator located in PJM is estimated to be less likely to announce retirement, relative to their regulated counterparts, neither unit is at risk.

Figure 7. Probability



The traits of the hypothetical average generator are as follows:

Variable	Mean
Size	361 MW
Age	43 years old
Capacity Factor	53%
EnvUpgradeCosts	$229/MW-d

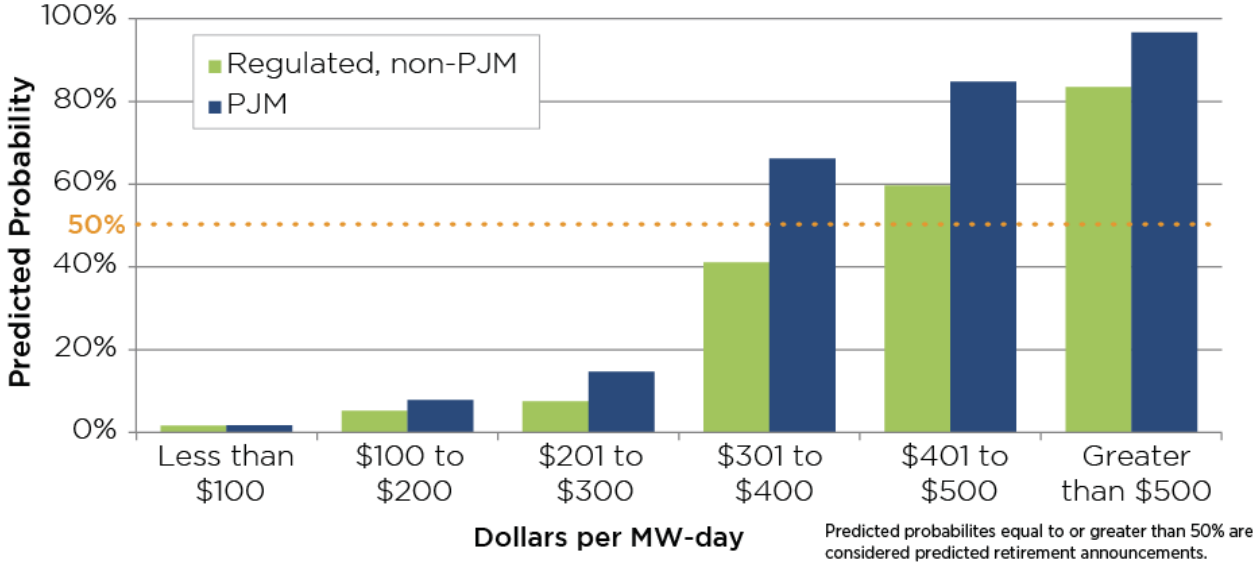
As expected, there is a positive relationship between age and the probability of announcing retirement. It is estimated that an increase of one year from the average age results in a 5.2 percent increase in the odds of retirement. When interacting age with the PJM variable, the model predicted that generators located within PJM's footprint retire older units at a faster rate, relative to generators located within regulated, non-PJM states.

Both size and capacity factor exhibit an inverse relationship with respect to retirement decisions. A one MW increase in size is estimated to result to less than a 1 percent decrease in the odds of retirement. When increasing plant size by 10 MW, the odds of retirement decreases by 1 percent. Likewise, a 1 percent increase in capacity factor leads to an estimated 2.9 percent decrease in the odds of retirement.

The model estimates that a $1/MW-day increase in environmental upgrade cost results in less than 1 percent increase in the odds of retirement. When increased by $10/MW-day, the odds of retirement increases by 5.1 percent. When interacting the MATS-associated environmental upgrade costs with PJM, this model estimates that unit retirements in the PJM footprint are more sensitive to cost increases relative to their regulated counterparts. That is, an increase in upgrade cost beyond the mean drives a higher increase in retirement share in PJM relative to regulated areas.

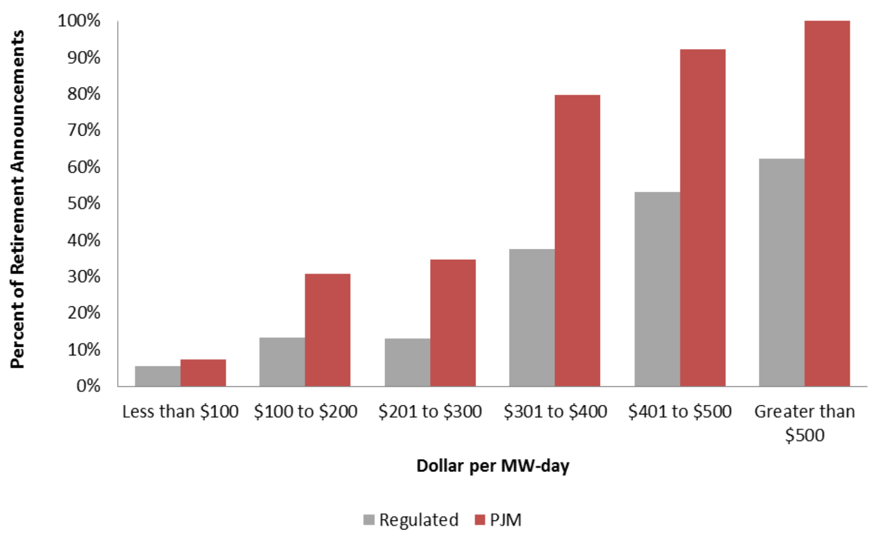
Figure 8 below compares average predicted probabilities of announcing retirement with respect to upgrade costs for PJM versus regulated generators. Each probability charted below is the average of the predicted probabilities for the actual units in each bin.

Figure 8. Predicted Probability of Retirement by Environmental Upgrade Cost: PJM vs non-PJM (2011-2016)



Generators with an estimated probability of 50 percent or more are predicted to retire. In general, the model does not expect generators with upgrade costs of less than $300/MW-day to retire. However, units with relatively high upgrade costs are predicted to retire, and those high-cost units located in PJM have a still higher probability of retirement. This suggests that PJM generation owners are less likely to keep very expensive units in operation, relative to owners in regulated environments. The retirement pattern estimated by the model closely follows what was actually observed, which is in Figure 9 below:

Figure 9. Observed Retirement by Environmental Upgrade Cost: PJM vs. Regulated Areas (2011-2016)



Sensitivities

Balanced Panel

To assess if the unbalanced panel introduced bias or inefficiency, the sample was restricted to include only units that remained in operation throughout the entire estimation period of 2011 to 2013. The model was then re-estimated with the restricted sample as otherwise previously specified.

Regulatory Environment

The definition of regulated was re-stipulated as a robustness check. In the original model, a generator was considered regulated if it was located outside PJM's footprint and able to recover costs by way of a regulated rate-of-return through customer rates. This included some generators that were located within an ISO/RTO and is discussed in depth in the Regulatory Environment description. To test for robustness in results with respect to the definition of regulated, the model was re-estimated excluding generators that are located outside of PJM but within an ISO/RTO.

Retirement Window

MATS required that generators come to compliance by April 2015, with conditional extensions into 2016. However, it is possible that some retirement announcements scheduled for beyond 2016 could be attributed to MATS. As an additional sensitivity, the retirement announcement window was broadened to encompass announcements until the end of 2019.

Estimation and Results

Table 7 below displays the sensitivity results in the following order: Sensitivity I re-estimates the original model with a restricted dataset that includes only generators that remained in operation during the full estimation period. Sensitivity II respecifies the original model but extends the retirement window to 2019. Finally, the definition of regulated is tested in which Sensitivity III has a retirement window of 2011 to 2016 and Sensitivity IV's retirement window ends in 2019.

Table 7. Odds Ratios for Sensitivity Analysis

Parameter	Description	Sensitivity I Odds Ratio	Sensitivity I Confidence Interval		Sensitivity II Odds Ratio	Sensitivity II Confidence Interval		Sensitivity III Odds Ratio	Sensitivity III Confidence Interval		Sensitivity IV Odds Ratio	Sensitivity IV Confidence Interval	
Intercept		0.001**	0.000	0.004	0.010**	0.004	0.026	0.040**	0.013	0.127	0.019**	0.006	0.058
PJM	Located within PJM footprint	0.061**	0.004	0.927	0.061**	0.010	0.393	0.215	0.043	1.084	0.063**	0.013	0.303
Age*PJM	Interaction variable	1.114**	1.090	1.138	1.087**	1.071	1.104	1.052**	1.033	1.072	1.071**	1.052	1.091
Age	Year - Unit In Service Year	1.042**	1.016	1.096	1.072**	1.030	1.115	1.045**	1.010	1.080	1.071**	1.036	1.108
Size	MW	1.000	0.999	1.001	0.999	0.998	1.000	0.999**	0.998	0.999	0.999	0.999	1.000
CapFac	%	0.071**	0.037	0.135	0.066**	0.038	0.114	0.072**	0.040	0.131	0.154**	0.088	0.268
EnviroCosts	20 Yr Capital Recovery, $MW-day	1.006**	1.005	1.007	1.005**	1.004	1.006	1.006**	1.005	1.008	1.005**	1.004	1.007
EnviroCosts*PJM	Interaction variable	1.006**	1.002	1.010	1.000	0.998	1.002	0.998	0.996	1.000	0.997**	0.996	0.999
		N = 2,442	**QICu**= 408.95		**N** =2,726	**QICu**= 507.79		**N** =2,018	**QICu**= 501.10		**N** =2,030	**QICu**= 563.94	
		Correctly estimated: 86.49%			**Correctly estimated**: 82.05%			**Correctly estimated:** 82.73%			**Correctly estimated**: 79.75%		

***significant at a 5% level*

Table 8. Title

Where the probability that a generator announces retirement is estimated given the following robustness checks:

Model	Change	Retirement Window	Definition of Regulated
Sensitivity I	Balanced panel	2014 to 2016	Regulated, non-PJM
Sensitivity II	Retirement window	2011 to 2019	Regulated, non-PJM
Sensitivity III	Regulated definition	2011 to 2016	Regulated, non-ISO/RTO
Sensitivity IV	Regulated definition & retirement window	2011 to 2019	Regulated, non-ISO/RTO

Sensitivity I: Balanced Panel

Results from the first sensitivity did not vary greatly from the original model, with the exception that the size variable was no longer statistically different from zero. The overall fit slightly improved and the model increased in accuracy by just less than two percentage points. Because the results are qualitatively similar and the standard errors and fit are generally stable, it is unlikely that the unbalanced panel is causing significant bias of loss of efficiency.

Sensitivity II: Retirement Window = 2011 to 2019

Extending the retirement window to end in 2019 produced similar estimated effects as the 2011 to 2016 model. As in the original model, the hypothetical average generator located in the PJM footprint is predicted to be less likely to retire, relative to the average generator located within a regulated environment. This model estimates that PJM tends to be more responsive to increases beyond the average age, relative to their regulated counterparts. Additionally, this sensitivity supports the original findings that there is a positive relationship between the probability of announcing retirement and both increases in age and MATS associated upgrade costs. Unlike the original model, however, size and a difference in the rate at which PJM responds to increased upgrade costs were not found to be statistically different from zero.

Sensitivity III: Regulated = regulated, non-ISO/RTO

The robustness of results with respect to the definition of regulated was tested in the final two sensitivities, in which "regulated" was re-specified to exclude generators located within an ISO/RTO. Sensitivity III mostly supported the previous findings. However, under this definition of "regulated," there was not a statistically significant difference in the odds of retirement for the average generator located within PJM, relative to a regulated environment. Likewise, this specification did not estimate a statistically significant difference in how responsive PJM is to increasing upgrade costs when compared to its regulated counterpart.

Sensitivity IV: Regulated = regulated, non-ISO/RTO & Retirement Window = 2011 to 2019

Sensitivity III was re-estimated with the retirement window if 2011 to 2019. Results for this final robustness check generally supported the original findings. Similar to Sensitivities I and II, size was found to have a statistically insignificant impact on the probability of announcing retirement. Unlike the previous sensitivities, however, the interaction of PJM and estimated MATS-associated upgrade costs was found to be negative and statistically significant. This finding is counter to the original model.

Table 9 below summarizes the general findings for all models:

Table 9. Results

Variable	Original Model	Sensitivity I	Sensitivity II	Sensitivity III	Sensitivity IV
PJM	Less likely	Less likely	Less likely	*No statistical difference*	Less likely
Age	**More likely**	**More likely**	**More likely**	**More likely**	**More likely**
Age*PJM	PJM is more responsive	PJM is more responsive	PJM is more responsive	PJM is more responsive	PJM is more responsive
Size	Less likely	*No statistical impact*	Less likely	Less likely	*No statistical impact*
Capacity Factor	Less likely	Less likely	Less likely	Less likely	Less likely
EnviroCosts	More likely	More likely	More likely	More likely	More likely
EnviroCosts*PJM	PJM is more responsive	PJM is more responsive	*No statistical difference*	*No statistical difference*	PJM is less responsive

Discussion and Conclusion

In general, these findings are consistent with the hypothesis that coal unit owners in PJM are more likely to make economically efficient decisions about retirement than those in regulated regions outside PJM.

The most direct finding supporting this hypothesis is the significant and positive value for the PJM term interacted with the environmental cost term. Holding all else equal in the regression model, the predicted probability of retirement of hypothetical units in PJM increases more sharply with increasing environmental costs relative to the same units in a regulated regime. That is, PJM units as a whole are more sensitive, and respond more sharply, to increases in environmental cost.

The strength of this finding is moderate. An increase of $10/MW-day from the average environmental upgrade cost of $229/MW-day results in an increase in the retirement rate for both PJM and regulated units. The resulting increase in the retirement rate of PJM units is 3 percent higher than the increase in the retirement rate of regulated units.

A seemingly contrary finding is that a hypothetical unit with average traits is predicted by the regression model to be 12.8 times less likely to retire in PJM than the same hypothetical unit in a regulated regime. This apparent contradiction is, in fact, an important finding. Consider that the average unit has a relatively low environmental upgrade cost, a relatively high capacity factor, and is unlikely to retire whether modeled in PJM or in regulated: 0.7 percent in PJM, and 8.7 percent in regulated. The average coal generation unit is economically efficient and generally remains in operation, and is significantly more likely to remain in operation in PJM than in regulated areas.

Three of the sensitivities tested are inconsistent with the hypothesis. These include both sensitivities that set the definition of “regulated” to exclude all RTOs, as well as the sensitivity with regulated equal to non-PJM but the consideration of MATS retirements extended to 2019. This reflects the moderate strength of the finding, as well as fundamental differences between sensitivities.

As follows, this analysis argues that the primary sensitivity is the most appropriate, and therefore most relevant, finding. First, 2016 is the most appropriate deadline for considering a retirement as being driven by MATS (since it is the last year that non-compliance is allowed). Second, units located in RTOs for which the generation mix is primarily driven by rate recovery, rather than market revenues, are most appropriately categorized as regulated units. Readers that disagree with these premises might instead favor the results of alternate sensitivities. Readers that find merit with all sensitivities might consider the moderate strength of the finding and conclude that there is no major difference in the investment decisions of coal units between PJM and regulated areas.

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