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The Real Options to Shutdown, Startup, and Abandon: U.S. Electricity Industry Evidence

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Abstract

The purpose of this paper is to examine empirically the partially irreversible decisions to shutdown, startup, and abandon existing production assets under cash flow uncertainty and regulatory uncertainty. We use detailed information for 1,121 individual electric power generators located in the U.S. for the period 2001–2009 and find strong evidence of real options effects. We find that both profitability uncertainty and regulatory uncertainty decrease the probability of shutdown. Regulatory uncertainty also decreases the probability of startup, but we find that cash flow uncertainty increases the probability of startup, especially for large generators.

Keywords: Regulatory uncertainty, real options, retail competition, stranded costs, investment decisions.
JEL: D81, E22, G31, L51, L94, Q41.

1. Introduction

The theory of real options predicts that, in the face of irreversible switching costs and uncertain cash flows, major changes in assets are subject to hysteresis, and can be structured as options.[1] A significant source of uncer-

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[1]See Dixit and Pindyck (1994) or Trigeorgis (1996) for textbook treatments.

tainty of particular interest to corporate decision makers is uncertainty about current and future policies and regulations. We study the effects of regulatory uncertainty on managers' decisions to shutdown, startup, and abandon (collectively *status changes*) existing production assets. We conduct our tests using detailed information for 1,121 individual electric power generators. To the best of our knowledge this is the first paper to study the effects of regulatory uncertainty on the decisions to shutdown, startup, and abandon.

The paper most closely related to ours is Moel and Tufano (2002) who evaluate empirically the predictions of the Brennan and Schwartz (1985) real options model by examining the shutdown and startup decisions for 285 gold mine properties during the 1988–1997 time period.[2] Our work differs from Moel and Tufano (2002) in important ways. In addition to having a much larger and richer data set, we focus on the effects of regulatory uncertainty, while Moel and Tufano (2002) consider only cash flow uncertainty due to fluctuating gold prices. Also, we examine the option to abandon.

The setting for our study is deregulation in retail electricity markets in the United States. Retail electricity prices vary greatly across individual states and these differences have implications for the competitive positions of firms in electricity-intensive industries. As a result some states have decided to allow retail electricity customers to select their suppliers, i.e., to introduce retail competition. Uncertainty about retail competition implies uncertainty about the values of existing assets. Real options theory suggests that uncertainty should delay investment decisions while managers wait for more information. We therefore expect that the presence of regulatory uncertainty should decrease the probability of status changes.

We find that regulatory uncertainty reduces the probability of both startups and shutdowns. We find no effect of regulatory uncertainty on the decision to abandon a generator. We believe this is because the generators in our sample which were abandoned were relatively old, small, and inefficient.

We also study the effects of cash flow uncertainty. An electric power generator comprises a series of call options written on the spark spread.[3]

[2]Fleten and Näsäkkälä (2010) consider investments in new gas-fired generators under uncertain electricity and natural gas prices. They conclude that operating flexibility and the abandonment option interact such that their joint value is less than their separate values, and that operating flexibility significantly impacts the value and decision to build a generator.

[3]The spark spread is the difference between the value of electricity and the cost of the

Spark spread volatility (our measure of cash flow uncertainty) thus has two effects on the decision to make a status change. First, increased uncertainty increases the value of waiting for more information as in a traditional real options framework. We refer to this as the *information effect*. Second, because a plant is itself an option on the spark spread, increased volatility increases the option value of the plant. We refer to this as the *option value effect*.

Both the information effect and the option value effect imply that cash flow uncertainty should reduce the probability of shutdown and abandonment. We confirm both in our data using formal hypothesis tests. That is, cash flow uncertainty reduces the probability of shutting down an operating generator, and, cash flow uncertainty reduces the probability of abandoning a generator which was previously shutdown.

The effect of cash flow uncertainty on the startup decision is less clear. Consider a generator which was previously shutdown. The information effect should make it less probable that the generator will be restarted. But the option value effect should make it more probable that the generator will be restarted. Similar to Lund (2005), the overall effect of increased uncertainty on the decision to restart an electric power generator is ambiguous.[4]

We find that cash flow uncertainty increases the probability of startup, particularly for large generators. That is, our results provide evidence that the option value effect dominates the information effect.

2. Regulatory Uncertainty

The introduction of retail competition allows end-users to choose electricity suppliers.[5] The prospect of competition at the retail level leaves utilities in the position of possibly losing (or gaining) customers. If the utility loses some of its existing customers when retail competition is implemented, then a generator which was profitable in the regulated world might no longer be needed. Such a generator is referred to as a stranded asset and the associated

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fuel required to generate it.

[4]Lund (2005) demonstrates that, while increased uncertainty increases the trigger level for investment, it also increases the probability that the level will be reached. He concludes that the sign of the effect of uncertainty on the decision to invest in ambiguous.

[5]An excellent overview of retail deregulation of electricity markets can be found in Joskow (2008).

costs are referred to as stranded costs.[6]

The decision to introduce retail competition is in the purview of the individual State Utility Commissions. The U.S. Energy Information Administration publishes a time line and descriptive summary of state-level retail competition activities. This information, supplemented by information available from state utility commissions, allows the construction of a state-level retail competition index.[7] The index is a discrete variable taking on values from 1 to 5, which correspond to:

1. no activity,
2. investigation underway,
3. competition recommended,
4. law passed requiring retail competition, and,
5. competition implemented.

The index measures the level of regulation. Our interest is in uncertainty. When the competition index takes a value of two, there is uncertainty about whether the state will implement retail competition and therefore uncertainty about the recovery of stranded costs. When the index takes a value of three, there is uncertainty about the specific form retail competition and stranded cost recovery ultimately will take. We define a regulatory uncertainty indicator variable which takes a value of one when the competition index above is equal to either two or three, and which takes a value of zero otherwise.[8]

$$\begin{aligned} REGUNCERT_{s,t} &= 1 \text{ if, for state } s \text{ in year } t\text{, the competition} \\ &\quad\ \text{index equals 2 or 3, and,} \\ &= 0 \text{ otherwise.} \end{aligned} \tag{1}$$

[6]According to the FERC (see the Code of Federal Regulations, 18 CFR 35.26) *"Retail stranded cost means any legitimate, prudent and verifiable cost incurred by a public utility to provide service to a retail customer that subsequently becomes, in whole or in part an unbundled retail transmission services customer of that public utility."* In our context, the customer ceases to purchase electricity from the utility, but still uses the utility's transmission system to deliver the electricity. Thus one or more generators may become stranded assets.

[7]A similar index was developed independently by Delmas and Tokat (2005).

[8]For robustness we also repeated the regression analyses below with a modified version of the regulatory uncertainty indicator. The modified version of the indicator variable is set equal to zero for any state which is in the bottom 25% of retail electricity prices. Our results are unchanged.

Craig and Savage (2013) find that, in order for the effects of restructuring to take effect, a generator needs to be subject to competition at both the wholesale and retail level. Our sample includes only those generators which are located in states which have active Regional Transmission Organizations (RTOs) and therefore already have wholesale markets. Uncertainty surrounding retail competition should then be relevant for decision makers at such generators.

Consistent with real options theory, we expect managers to be less likely to shutdown, startup, and abandon existing generators when there is uncertainty about the introduction of retail competition and the recovery of stranded costs.[9] In the empirical analyses below we formally test these hypotheses.

3. Data

Our primary data sources are the Energy Information Administration, NYMEX, the U.S. Environmental Protection Agency, and wholesale electricity market system operators. Interest rate data come from the U.S. Federal Reserve Bank. Table 1 presents summary statistics for generator-specific variables in our sample, while Table 2 presents summary statistics for macroeconomic, real options, and firm-specific variables.

The main data source for this paper is Form 860 collected and disseminated by the Energy Information Administration (hereafter EIA), the statistical arm of the U.S. Department of Energy. Form 860 contains detailed data for nearly every generator in the United States, both existing and planned.

We consider generators from three major wholesale electricity markets - Pennsylvania-New Jersey-Maryland (PJM), the New England Independent System Operator (ISO-NE), and the New York Independent System Operator (NYISO) - for the 2001–2009 time period.[10] The choice of areas and sample period is driven by (i) the availability of electricity price data and (ii)

[9]Reinelt and Keith (2007) study regulatory uncertainty and its effect on the social cost of carbon abatement. Linnerud et al. (2014) examine climate policy and find that the investment decisions of professional investors are consistent with a real options model, but that smaller, relatively unsophisticated investors ignore the value of optimal timing.

[10]Specifically, we include generators located in Connecticut, Delaware, Illinois, Indiana, Kentucky, Maine, Maryland, Massachusetts, Michigan, New Hampshire, New Jersey, New York, North Carolina, Ohio, Pennsylvania, Rhode Island, Tennessee, Vermont, Virginia, Washington D.C., and West Virginia.

significant changes in Form 860 beginning in 2001. We focus on "peaking" generators as these should be more subject to the factors expected to influence shutdown, startup, and abandonment decisions.[11] The final data set contains 8,189 generator-year observations on 1,121 individual generators.

3.1. Status Change Definitions

For our purposes, the key variable from EIA Form 860 is the "status" of the generator. The relevant status codes are

- OP - operating,
- SB - standby, and,
- RE - retired.

A generator which has status code OP is available for operation. A generator which has status code SB has been shutdown, or mothballed.[12] A generator which has status RE has been abandoned, or retired, and cannot return to service.

Consider a generator which is operating (status OP) in the current year. Next year, the generator may either continue to operate (remain in status OP) or move to standby (SB).[13] We define a "shutdown" to be movement from status OP in year t to status SB in year $t + 1$.[14] Table 3 documents the occurrence of shutdowns by year in our sample. For example, of the 832 generators which were operating in 2004, 820 continued to operate in 2005

[11]We retain only simple cycle combustion turbines (CT). The fuel type is either low sulfur fuel oil (DFO), i.e., EIA fuel types **DFO**, **FO1**, **FO2**, or **FO4**, or natural gas (NG). Baseload technologies, such a coal-fired and nuclear generators, operate more-or-less continuously for the duration of their useful lives.

[12]The EIA provides variable definitions in a *Layout* file accompanying the EIA 860 data. The 2000 *Layout* file (status code SB is not defined in the *Layout* file for the 2001 and 2002 years) defines SB as "*Cold Standby (Reserve): deactivated (mothballed), in long-term storage and cannot be made available for service in a short period of time, usually requires three to six months to reactivate.*"

[13]While it is possible to move directly from status OP (operating) to status RE (retired), such moves are rare and often driven by other circumstances, such as catastrophic failure.

[14]It is conceivable that the status of a generator could change more than once per year. The annual frequency of our data is not fine enough to observe such changes. Our results therefore provide a lower bound on the exercise of managerial flexibility. We thank Afzal Siddiqui for pointing this out.

while 12 were shutdown. For the full sample there are a total of 76 instances of shutdown versus 6,539 instances of a operating generator remaining in operating mode.

Consider a generator which was previously shutdown, i.e., a generator which is on standby (SB) in the current year. Next year the generator may either startup (move to status OP), remain shutdown (SB), or be abandoned (move to status RE). We define a "startup" to be movement from status SB in year t to status OP in year $t+1$. We define an "abandonment" to be movement from status SB in year t to status RE in year $t+1$. Table 4 documents occurrences of these alternatives by year in our sample. For example, of the 188 generators which were on standby in 2004, 153 were still on standby in 2005, 22 were started up, and 13 were abandoned. For the entire sample, there are a total of 184 instances of startup and 78 instances of abandonment.

3.2. Future Profitability

We use projected reserve margin as our proxy for expected future profitability. Reserve margin for region k and year t ($RM_{k,t}$) is defined to be

$$RM_{k,t} \equiv (C_{k,t} - D_{k,t})/D_{k,t}, \tag{2}$$

where $C_{k,t}$ is the year t capacity in region k and $D_{k,t}$ is the year t peak demand in region k, both measured in MW.[15] The raw data come from NERC's 2009 Electricity Supply and Demand (ES&D) database.

Because electricity cannot be stored, available supply (i.e., capacity) must always exceed contemporaneous demand in order to prevent blackouts. Lack of storability implies that, when demand approaches available supply, electricity prices increase at an increasing rate.[16] The lower is the reserve margin, the less excess capacity there is in the system, and the higher are wholesale electricity prices. Projected reserve margin therefore acts as an (inverse) proxy for expected future profitability of the generator. Low reserve margins imply high future profitability and vice versa.[17]

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[15]For planning purposes, target reserve margin values range from 15% to 20%. Table 2 shows that the mean reserve margin observed in our sample is 19.8%. The minimum and maximum observed reserve margins are 11.5% and 30.1%, respectively.

[16]See, for example, Bessembinder and Lemmon (2002) or Mount et al. (2006).

[17]There are other channels through which generators can earn income. Spinning reserve

3.3. Portfolio Effects

The decision to shutdown, startup, and/or abandon an electric power generator may depend on the size of the firm. A firm which owns a large amount of capacity may be able to reassign workers when it makes the decision to shutdown or abandon an existing generator, whereas a smaller firm may be forced to layoff workers. As pointed out by Moel and Tufano (2002), large firms have greater opportunity to subsidize less profitable generators. We use two measures of firm size, the total capacity owned by the firm and the total number of generators owned by the firm. The summary statistics in Table 2 show that there is a great deal of variation in the size of the firms in our sample. The mean number of generators owned by each firm in our sample is 15.5, however there are 27 firms which own only one generator.

3.4. Generator Efficiency

Kovenock and Phillips (1997) emphasize the importance of controlling for generator efficiency in investment and abandonment decisions. The efficiency of an electric power generator is measured by its *heat rate*. The heat rate of generator i, HR_i, is the amount of fuel, measured in millions of British thermal units ($MMBtu$), required to generate one unit of electricity, measured in megawatt hours (MWh). A lower number indicates greater efficiency.

We use two sources for heat rate data. Our primary source is the Continuous Emissions Monitoring Systems (CEMS) data from the U.S. Environmental Protection Agency. CEMS data are available for 631 of the 1,121 generators in our sample. Heat rate data were included in Form 860 for 1990-1995. These data are available for 312 generators for which no CEMS data are available. Heat rates for the remaining 178 generators are estimated based on the age and size of the generator. Details are in Appendix A.

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refers to generators which are synchronized with the system but are not operating at full capacity. These generators can be ramped up significantly (within 10 minutes) if needed, e.g., when another generator suffers a forced (unexpected) outage. The generators in our study may sometimes be providing spinning reserve (though we have no way of knowing if and/or when), but they are more likely to be providing Non-Synchronous-Reserve, or NSR. A generator which is not synchronized to the system (which usually means it is offline) but which can be started quickly and produce output within 10 minutes is said to provide NSR. Until the year 2012 NSR was not compensated in PJM. Capacity markets, such as the Reliability Pricing Mechanism in PJM which came into existence 2007, were in their infancy at the end of our sample. We repeat the regressions below omitting years after 2007 with no material effect on the results.

For ease of interpretation, we convert heat rates into energy conversion efficiencies. Heat rates have units of $\frac{MMBtu}{MWh}$. Both $MMBtu$ and MWh measure energy. There are 3.41275 $MMBtu$ in one MWh. We convert heat rate into conversion efficiency as

$$EFF_i = \frac{3.41275}{HR_i} * 100\% \tag{3}$$

where EFF_i is the conversion efficiency of generator i which has heat rate HR_i. For example, a generator with a heat rate of 10 $MMBtu/MWh$ has a conversion efficiency of 34.1%. Summary statistics for efficiency (in %) are presented in Table 1.

3.5. Cash Flow Volatility

The cash flow for a generator is determined by the spark spread, the difference between the price of electricity and the cost of the fuel used to produce it. A peaking generator can be viewed as a collection of daily European call options on the spark spread.

Consider generator i which has heat rate HR_i, burns fuel j, and is located in region k. We calculate the generator-specific spark spread expressed in units of dollars per megawatt hour ($/MWh), for day n as

$$SPRD_{ijk,n} = P^{elec}_{k,n} - HR_i * P^{fuel}_{j,n}, \tag{4}$$

where $P^{elec}_{k,n}$ is the day n electricity price ($/MWh) in region k and $P^{fuel}_{j,n}$ is the day n fuel price ($/MMBtu) for fuel j. Daily spot prices for New York Harbor No. 2 Oil and NYMEX Henry Hub natural gas are taken from the EIA website. Electricity prices come from the PJM, ISO-NE, and NYISO websites.[18]

Spark spread volatility is then the standard deviation of the daily spark spread over year t.

$$SPRDSD_{ijk,t} = STDEV^{T}_{n=1}\big(SPRD_{ijk,n}\big), \tag{5}$$

where T is the number of days in year t.

[18]Consistent with our focus on peaking generators, we use electricity prices for the peak period of the day, defined to be the 16 hour period from hour ending 7 through hour ending 22. We obtain daily peak prices by taking the simple average of the hourly spot prices during the peak period.

3.6. Time Sequence of Data Availability

Consider as an example status changes which take place during the 2005 calendar year and therefore show up in the 2006 Form 860. In the regressions which follow we use only those data which were available as of the end of 2004 as explanatory variables for status changes (shutdown, startup, or abandonment) which occur during 2005.

4. Shutdown

In this section we examine the decision to shutdown an operating generator, i.e., to move from status code OP to status code SB. In the case of peaking generators such as those in our sample, there are two distinct shutdown options, one in the short term and one in the longer term.

Tseng and Barz (2002) study the option to shutdown an operating generator in the short term. That is, they consider hourly fuel prices and electricity prices, along with operational constraints, to study the option to turn off, or cycle, an operating generator. Short term cycling of generators is different than the long term shutdown considered in our paper. A generator which cycles offline overnight still has status OP. We study the long term option to mothball, or layup, an exiting generator. When a generator moves from status OP to status SB, the generator is no longer **available** to run.

Table 5 presents comparative univariate statistics for generators which were shutdown and those which continued to operate. The descriptive variables are divided into four categories - macroeconomic, firm-specific, generator-specific, and real options, i.e., measures of uncertainty. The last column presents differences. All of these differences are significant at the 1% or 5% level.

Beginning with the macro variables, generators tend to shutdown when projected reserve margins are high. High reserve margins imply low future profitability. Generators are more likely to be shutdown when expected future profitability is low.

We expect interest rates to have a positive relationship with shutdowns. The higher are interest rates, the lower is the present value of future cash flows, and the higher should be the probability that a generator will shutdown. The univariate statistics in Table 5 suggest exactly the opposite - generators tend to shutdown when interest rates are lower. However, reserve margin and interest rates are negatively correlated.[19] We believe that, when considered in isolation, interest rates are simply proxying for reserve margin. The multivariate analysis below supports this conjecture. When we control for reserve margin, interest rates and shutdown probabilities are positively related.

The firm-specific variables are the total capacity (in units of MW) owned by the firm and the total number of generators owned by the firm. Table 5 indicates that firms which shutdown generators tend to be much smaller than firms which continue to operate existing generators, as measured both by total capacity owned and by total number of generators.[20]

Turning to the generator-specific variables, generators which shutdown are on average older, less efficient, and smaller than generators which continue to operate.

Spark spread (cash flow) volatility and the regulatory uncertainty indicator variable are both measures of uncertainty and ought to matter if real options effects are important. Consistent with real options theory, Table 5 shows that shutdowns are more likely when (i) spark spread volatility is lower, and, (ii) there is less uncertainty about retail competition and the recovery of stranded costs. Average spark spread volatility for generators which shutdown is 31% less than spark spread volatility for generators which continue to operate.

Of the total generator-year 8,189 observations, 20.5% occur during times of regulatory uncertainty. Table 5 shows that, of the 76 individual instances of shutdown in our sample, only one ($\frac{1}{76} = 0.013$) occurs during a time of regulatory uncertainty. These univariate statistics provide strong circumstantial evidence for the existence of real options effects. Next we turn to a

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[19] Slower economic growth means slower growth in the demand for electricity and therefore higher reserve margins. Slower economic growth also tends to reduce interest rates. In our data the simple correlation coefficient between interest rates and reserve margin is -0.35.

[20] We think there are at least two potential explanations for this effect. First, smaller firms have fewer opportunities to subsidize less profitable generators. Second, and perhaps more important, many of the small firms in our sample are firms whose primary business is not electricity generation. These firms do not have the same level of in-house maintenance expertise as do firms whose primary business is electricity generation. When the generators owned by these firms age and become relatively less cost effective, it is more costly for these small firms to undertake the maintenance required to keep the generator operational, hence they are more likely to shutdown the generator.

multivariate analysis.

4.1. Binary Logit Regression

Consider generator i which burns fuel j and is located in region k. We begin our multivariate analysis using a binary logit specification, as follows.

$$\begin{aligned} I^{SB}_{i,t+1} &= \alpha + (\beta_1 * RM_{k,t+1}) + (\beta_2 * T10_t) + (\beta_3 * EFF_i) + (\beta_4 * SIZE_i) \\ &\quad +(\beta_5 * TOTCAP_{i,t}) + (\beta_6 * SPRDSD_{ijk,t}) \\ &\quad +(\beta_7 * REGUNCERT_{s,t}), \end{aligned} \tag{6}$$

where

$I^{SB}_{i,t+1}$ is an indicator variable which takes the value of zero if generator i was operating in year t and operating in year $t+1$, and which takes a value of one if generator i was operating in year t and shutdown in year $t+1$,[21]

$RM_{k,t+1}$ is the projected reserve margin for region k and year $t+1$,

$T10_t$ is the ten year treasury rate for year t,

EFF_i is the efficiency of generator i,

$SIZE_i$ is the capacity of generator i,

$TOTCAP_{i,t}$ is the year t total capacity owned by the firm which owns generator i,

$SPRDSD_{ijk,t}$ is the standard deviation of year t spark spread for generator i which burns fuel j and is located in region k, and,

$REGUNCERT_{s,t}$ is an indicator variable which takes a value of one if there is regulatory uncertainty in state s (in which generator i resides) and year t, and, a value of zero otherwise.

The last two regressors, $SPRDSD$ and $REGUNCERT$, are measures of uncertainty and should matter if plant managers consider real options effects when making shutdown decisions. Table 6 presents the results. The

[21] All the generators in this regression were operating (OP) in year t.

table presents the average marginal effects $\left(\partial Prob(I^{SB}=1)/\partial x\right)$ of each independent (x) variable. For the indicator variable $REGUNCERT$ the table presents the change in the probability of a shutdown when the variable changes from zero to one.

4.2. Individual Regressions

We begin by including each independent variable separately. Each coefficient is significant and the signs are consistent with the summary statistics in Table 5. Considering each explanatory variable separately allows us to get a feel for which is most important. Expected future profitability has the most explanatory power for the shutdown decision. Among the individual regressions, the RM regression has the greatest psuedo-R^2 (14.3%), the greatest log-likelihood, and the lowest values for both information criteria statistics, AIC and BIC. The coefficient on RM is positive indicating that generators are more likely to be shutdown when there is greater excess capacity. As discussed above, higher reserve margins imply lower wholesale electricity prices and therefore less valuable generators. Generators tend to shutdown when expected future profitability is low.

Regarding cash flow uncertainty and regulatory uncertainty, we formulate null (uncertainty has no effect) and alternative (our prior, that uncertainty reduces the probability of shutdown) hypotheses to be consistent with the standard real options result that uncertainty should delay investment, as follows.

***H*1**: Cash flow uncertainty.

$H1_o : \beta_6 = 0$ (Cash flow uncertainty has no effect on shutdown.)

$H1_a : \beta_6 < 0$ (Cash flow uncertainty decreases the probability of shutdown.)

***H*2**: Regulatory uncertainty.

$H2_o : \beta_7 = 0$ (Regulatory uncertainty has no effect on shutdown.)

$H2_a : \beta_7 < 0$ (Regulatory uncertainty decreases the probability of shutdown.)

The coefficients for the real options variables $SPRDSD$ ($\beta_6 = -1.016$) and $REGUNCERT$ ($\beta_7 = -0.014$)are negative and significant. We reject null hypotheses $H1_0$ and $H2_0$ in favor of the alternatives, each at the 1% level. Increases in spark spread volatility and regulatory uncertainty each reduce the probability of shutting down an operating generator.

4.3. Full Regression

The last column of Table 6 shows that, with one exception, the insights gained from the individual regressions continue to hold when all the independent variables are included in the same regression.[22] Most importantly, the coefficients on $SPRDSD$ ($\beta_6 = -0.609$) and $REGUNCERT$ ($\beta_7 = -0.012$)remain negative and significant. We reject null hypotheses $H1_0$ at the 5% level and $H2_0$ at the 1% level. Consistent with our priors, increases in either spark spread volatility or regulatory uncertainty decrease the probability of shutting down an operating generator even when we control for other factors likely to affect the shutdown decision.

Figure 1 plots the probability of shutdown as a function of reserve margin, based on the regression results from Table 6. The top panel presents the probability of shutdown for the cases of regulatory uncertainty (blue circles) and no uncertainty (red squares). At low values of reserve margin (high future profitability), the probability of shutting down an operating generator is near zero regardless of the regulatory environment.

At higher values of reserve margin (lower values of future profitability) the probability of shutting down an operating generator increases dramatically, but only for the case in which there is no regulatory uncertainty. In the presence of regulatory uncertainty the probability of shutting down an operating generator is small for any value of reserve margin. Uncertainty about retail competition and the recovery of stranded costs translates into uncertainty about generator profitability, hence generator owners are more hesitant to shutdown operating generators.

The bottom panel of Figure 1 presents the probability of shutting down an operating generator as a function of reserve margin for three values of spark spread volatility - \$10/MWh (blue circles), \$30/MWh (red squares), and \$100/MWh (green triangles).[23] When reserve margin is low (future profitability is high), the probability of shutting down an operating generator is small, irrespective of spark spread volatility. In this case the spark spread options which comprise the generator are effectively in-the-money and optionality constitutes a relatively small part of the generator's value, so spark spread volatility is less important to the shutdown decision.

[22] The exception is that the sign of $T10$ changes from negative to positive, consistent with our priors about the effect of interest rates on the option to shutdown.

[23] We choose to use \$10/MWh, \$30/MWh, and \$100/MWh in Figure 1 to approximately represent the minimum, mean, and maximum values observed in our sample. See Table 2.

When reserve margin is high (future profitability is low), the spark spread options which comprise the generator are out-of-the-money, optionality is the main source of the generator's value, and spark spread volatility is very important to the shutdown decision. When spark spread volatility is high, the option value of the generator is correspondingly high and the probability of shutdown is near zero regardless of reserve margin. When reserve margin is high and spark spread volatility is low, the options which comprise the generator are both out-of-the-money and the volatility of the underlying asset is low, rendering the options nearly worthless. As Table 6 and Figure 1 make clear, these effects are both statistically and economically significant.

5. Startup and Abandonment

In this section we examine the decisions to startup and abandon a generator which was previously shutdown. Table 7 presents comparative univariate statistics for generators which are in the shutdown mode in year t and either (i) remain shutdown (SB), (ii) startup (OP), or (iii) are abandoned (RE) in year $t + 1$. For those generators which either startup or are abandoned, the table presents differences relative to generators which remain shutdown.

5.1. Startup

Consider first generators which startup. Generators tend to startup when projected reserve margins are low and therefore expected future profitability is high. Consistent with the discussion above, we expect startups to be more likely when interest rates are low and therefore the present value of future cash flows is high. Table 7 shows exactly the opposite - startups tend to happen when interest rates are high, again reflecting the negative correlation between interest rates and reserve margin. Table 7 also shows that firms which restart generators are not significantly different in size than firms for which generators remain shutdown, as measured by either total capacity or total number of generators. Generators which startup are on average younger, more efficient, and larger than generators which remain shutdown.

Important determinants of the decision to shutdown and/or startup a generator should include the costs involved in doing so. We proxy for startup costs by calculating the amount of time (in years) that a generator has been shutdown. The longer a generator has been out of service, the greater should be the startup cost. In general, the cost to shutdown a generator is small relative to the cost to restart a generator. The cost to restart varies with the level of maintenance performed while the generator is out of service, and therefore is a function of managerial priorities. We ignore the cost to shutdown and we focus on one single technology (simple cycle combustion turbines), thereby eliminating variation across technology types.[24] Generators which startup have been shutdown for a shorter period of time (1.16 years) than generators which remain shutdown (2.55 years) indicating that generators which startup have lower startup costs than generators which remain shutdown.

Turning to the real options variables, Table 7 shows that generators which startup have higher spark spread volatility than generators which remain shutdown. While increased cash flow uncertainty increases the value of waiting for more information (information effect), increased cash flow uncertainty also increases the value of the call options which comprise the generator (option value effect). The univariate data suggest that the option value effect is stronger that the information effect for the startup decision, at least in our sample.

Table 7 also shows that startups tend to occur when there is no regulatory uncertainty. Of the 184 total instances of startup in our sample, only eight ($\frac{8}{184} = 0.043$) took place during a time of regulatory uncertainty.

5.2. Abandonment

Next consider generators which are abandoned. The last two columns of Table 7 show that generators tend to be abandoned when projected reserve margins are high and expected future profitability therefore is low. Firms which abandon generators tend to be much (three to four times) larger than those which do not.

Abandonments take place when spark spread volatility is low and when there is no regulatory uncertainty. Specifically, spark spread volatility for generators which are abandoned is 27.5% less than spark spread volatility for generators which remain shutdown. Only two of the total 78 abandonments ($\frac{2}{78} = 0.026$) in the sample took place during times of regulatory uncertainty.

5.3. Startup and Abandonment Multinomial Logit Regression

We use a multinomial logit regression to examine startup and abandonment decisions. The advantage of a multinomial logit regression is that it

[24] A more detailed discussion based upon conversations with industry experts can be found in Appendix B. We thank Steve Marshall of Lakeland Electric and Paul D. Clark II of the City of Tallahassee for sharing their insights and experience.

allows us to consider the startup and abandonment decisions simultaneously.

$$
\begin{aligned}
I^{OPRE}_{i,t+1} = {} & \alpha + (\beta_1 * RM_{k,t+1}) + (\beta_2 * T10_t) + (\beta_3 * EFF_i) + (\beta_4 * SIZE_i) \\
& + (\beta_5 * TOTCAP_{i,t}) + (\beta_6 * SBTIME_{i,t}) \\
& + (\beta_7 * SPRDSD_{ijk,t}) + (\beta_8 * REGUNCERT_{s,t}), \qquad (7)
\end{aligned}
$$

where

$I^{OPRE}_{i,t+1}$ is a discrete variable which is equal to zero if generator i was on standby in year t and operating in year $t+1$, equal to one if generator i was on standby both in year t and in year $t+1$, equal to two if generator i was on standby in year t and retired in year $t+1$,[25]

$SBTIME_{i,t}$ is the length of time, in years, that generator i has been shutdown as of year t,

and all the other variables are as defined above. The results are presented in Table 8.[26] The table presents the average marginal effects $\left(\partial Prob(I^{RE} = 1)/\partial x\right)$ of each independent (x) variable. For the indicator variable $REGUNCERT$ the table presents the change in the probability of an abandonment when the variable changes from zero to one.

5.3.1. Startup results

We formulate null and alternative hypotheses for the effects of both cash flow uncertainty and regulatory uncertainty on startup as follows.[27]

***H*3**: Cash flow uncertainty - Startup.

$H3_o : \beta_7 = 0$ (Cash flow uncertainty has no effect on startup.)
$H3_a : \beta_7 > 0$ (Cash flow uncertainty increases the probability of startup.)

[25] All the generators in this regression had been previously shutdown (status SB) in year t.

[26] The startup (top panel) and abandonment (middle panel) results in Table 8 are from one multinomial logit regression. That is, each column in Table 8 reports the outcome of a single regression, the goodness of fit statistics for which are reported in the lower panel.

[27] As discussed above, the effect of cash flow volatility on startup is ambiguous. Based upon the univariate statistics in Table 7, we set the alternative hypothesis $H3_a$ such that $\beta_7 > 0$.

$\boldsymbol{H4}$: Regulatory uncertainty - Startup.

$H4_o : \beta_8 = 0$ (Regulatory uncertainty has no effect on startup.)
$H4_a : \beta_8 < 0$ (Regulatory uncertainty decreases the probability of startup.)

The top panel of Table 8 presents regression results for startup from equation (7). As was the case for shutdowns, the individual regressions show that expected future profitability is the single most important factor driving startups. The last column presents the results for the full model. The key drivers of the startup decision are expected future profitability (RM), generator size ($SIZE$), startup costs ($SBTIME$), and regulatory uncertainty ($REGUNCERT$). Startups are more likely when expected future profitability is higher, for larger generators, and when startup costs are lower.

In the individual startup regression (top panel of Table 8) the coefficient on $SPRDSD$ ($\beta_7 = 1.725$) is positive and significantly different from zero, again suggesting that the option value effect is stronger than the information effect. Based on this individual regression we reject $H3_0$ at the 1% level. In the overall regression, the coefficient on spark spread volatility ($\beta_7 = 0.613$) is reduced in magnitude from the individual regression and we are able reject $H3_0$ at only the 10% level.

We perform binary logit regression for startup, similar to the full shutdown regression reported in Section 4, with the sample limited to generators larger than 25 MW. (Small generators tend to be old and inefficient, thereby reducing the option value effect.) In order to save space we do not report the results in a table. In contrast to the results presented in Table 8, the coefficient on $SPRDSD$ (from the full regression) is $\beta_7 = 2.455$ and significant at the 1% level. We reject $H3_0$ in favor of the alternative. Cash flow uncertainty increases the probability of startup. The option value effect dominates the information effect, at least in our sample.

Also from the top panel of Table 8 we see that the coefficient on $REGUNCERT$ ($\beta_8 = -0.064$) is negative. We reject $H4_0$ in favor of the alternative at the 1% level. Regulatory uncertainty reduces the probability of starting up a generator which was previously shutdown.

5.3.2. Abandonment results

We formulate null and alternative hypotheses for the effects of both cash flow uncertainty and regulatory uncertainty on abandonment as follows.

***H*5**: Cash flow uncertainty - Abandonment.

$H5_o : \beta_7 = 0$ (Cash flow uncertainty has no effect on abandonment.)
$H5_a : \beta_7 < 0$ (Cash flow uncertainty decreases the prob. of abandonment.)

***H*6**: Regulatory uncertainty - Abandonment.

$H6_o : \beta_8 = 0$ (Regulatory uncertainty has no effect on abandonment.)
$H6_a : \beta_8 < 0$ (Regulatory uncertainty decreases the prob. of abandonment.)

The middle panel of Table 8 presents the results for abandonment. The key drivers of the abandonment decision are generator size ($SIZE$), firm size ($TOTCAP$), startup cost ($SBTIME$), and spark spread volatility ($SPRDSD$).

The coefficient on $SPRDSD$ is negative and significant at the 1% level in both the individual regression ($\beta_7 = -3.229$) and the full regression ($\beta_7 = -1.367$). We reject $H5_0$ in favor of the alternative. Higher spark spread volatility decreases the probability of abandonment through both the information effect and the option value effect.

In the full model, regulatory uncertainty is not important for making the abandonment decision. We cannot reject $H6_0$. We speculate that, because generators which were previously shutdown are "out of the game" already, abandoning the generator has little effect on the firm's cash flows. The prospect of losing customers with the advent of retail competition is therefore less important for abandonment decisions.

5.3.3. Graphical Representation

Figure 2 plots, on the same graph, the probabilities of startup (OP, red squares), shutdown (SB, blue circles), and abandonment (RE, green triangles) as a function of reserve margin, based upon the full regression (last column) in Table 8.

The upper panel presents the cases of regulatory uncertainty (right) and no uncertainty (left). Comparison of the upper panels shows that the existence of regulatory uncertainty has little effect on the probability of abandonment. The probability of abandonment (green triangles) is nearly identical in the upper left and upper right panels.

However, the probability of startup (red squares) is noticeably reduced in the presence of regulatory uncertainty (upper right panel) relative to the case of no uncertainty (upper left panel). When generator owners are uncertain about retail competition and stranded costs, they delay the decision to restart generators which may otherwise have restarted.

This result has important implications for regulators. Figure 2 shows that regulatory uncertainty significantly reduces the probability of startup when reserve margins are low. This is exactly the time when these generators are needed for system reliability.

The lower panel of Figure 2 presents the cases of low ($10/MWh, left) and high ($100/MWh, right) spark spread volatility. Comparison of the lower left and lower right panels of Figure 2 shows that spark spread volatility has a significant impact on the probability of abandonment. When spark spread volatility is low, the option value of the generator is low and the probability of abandonment (green triangles) increases as reserve margin increases. However, when spark spread volatility is high, the option value of the generator is high and the probability of abandonment is small regardless of reserve margin. This effect is statistically and economically significant.

6. Conclusions

Our results provide evidence that managers recognize and react to uncertainty in the regulatory environment in a way which is consistent with real options theory. Indecision on the part of regulators implies uncertainty about generator values. In the face of this uncertainty managers make fewer changes to the status quo.

The effect of cash flow uncertainty on the decision to startup is not clear a priori. The value of waiting for more information reduces the probability of startup. We refer to this as the information effect. Because an electric power generator is itself a call option, increased cash flow volatility increases the value of the generator. We refer to this as the option value effect. The option value effect suggests that increased cash flow uncertainty should increase the probability of startup. Our empirical analysis indicates that, at least in our sample, the option value effect dominates the information effect, particularly for large generators.

Importantly, regulatory uncertainty reduces the likelihood of startup when projected reserve margins are low. This is the time when system reliability is most threatened. When reserve margins are low, system reliability is in danger, and regulatory uncertainty makes the problem worse.

Acknowledgments

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Table 1: Generator Summary Statistics

The table presents summary statistics for the age (to the nearest year), size (megawatts, MW), and efficiency (%) of generators in the sample. The ages are calculated based upon the first year a generator appears in the sample.

	Age (yrs)	Size (MW)	Efficiency
NOBS	1,121	1,121	1,121
Mean	18.6	43.1	24.7%
Stdev	14.1	41.0	4.6%
Min	0	0.4	5.4%
Max	60	246.0	41.8%

Table 2: Macro, Real Options, and Firm Summary Statistics

The table presents summary statistics for macroeconomic, real options, and firm-specific variables. *RM* is reserve margin. *T10* is the ten year treasury bond rate. *SPRDSD* is the standard deviation of the spark spread, expressed in units of $/MWh. *REGUNCERT* is an indicator variable which takes the value of one during periods of regulatory uncertainty; see the discussion in Section 3 for details. *TOTCAP* is the average (over years) total capacity owned by the firm, expressed in units of MW. *TOTPLT* is the average (over years) total number of generators owned by the firm.

	Macro		**Real Options**		**Firm**	
	RM	*T10*	*SPRDSD*	*REGUNCERT*	*TOTCAP*	*TOTPLT*
NOBS	24	8	8,189	161	212	212
Mean	19.8%	4.71%	$31.19	0.217	1,388	15.5
Stdev	5.3%	0.62%	$15.23	0.414	2,984	24.4
Min	11.5%	4.01%	$12.07	0	1	1
Max	30.1%	6.03%	$187.44	1	21,561	202

Table 3: Shutdown: Transitions from OP to OP/SB by Year

Number of generators classified as operating (OP) in the *from year* and either operating (OP) or shutdown (SB) in the *to year*.

from year	*to year*	OP	SB	Total
2001	2002	695	2	697
2002	2003	803	1	804
2003	2004	808	43	851
2004	2005	820	12	832
2005	2006	829	16	845
2006	2007	848	0	848
2007	2008	851	2	853
2008	2009	885	0	885
	Total	6,539	76	6,615

Table 4: Startup and Abandonment: Transitions from SB to OP/SB/RE by Year

Number of generators classified as shutdown (SB) in the *from year* and either operating (OP), shutdown (SB), or retired (RE) in the *to year*.

from year	*to year*	OP	SB	RE	Total
2001	2002	60	221	1	282
2002	2003	47	198	1	246
2003	2004	9	143	49	201
2004	2005	22	153	13	188
2005	2006	1	158	6	165
2006	2007	6	173	0	179
2007	2008	32	139	2	173
2008	2009	7	127	6	140
	Total	184	1,312	78	1,574

Table 5: Shutdown: Univariate Statistics

Conditional on a generator operating in year t, the table presents statistics for macroeconomic variables, firm-specific variables, generator-specific variables, and real options variables (i.e., measures of uncertainty) for generators which continued to operate (did not shutdown, OP) in year $t+1$ and those which shutdown (SB) in year $t+1$.

Type	**Variable**	**OP**	**SB**	**delta**
Macro	Reserve Margin (%)	19.1%	26.9%	-7.8%***
	Interest Rate (%)	4.68%	4.49%	0.19%***
Firm	Total Capacity (MW)	6,210	2,469	3,741***
	Total Number of generators	56.5	28.4	28.2***
Generator	Age (years)	21.4	24.4	-3.1**
	Efficiency (%)	24.8%	23.4%	1.4%**
	Size (MW)	45.1	31.9	13.3***
Real Options	Spark Spread Stdev ($/MWh)	$31.04	$21.37	$9.66***
	Regulatory Uncertainty Dummy	0.240	0.013	0.227***
NOBS		6,539	76	

Table 6: Shutdown Binary Logit Estimation Results

Consider generator i which burns fuel j and is located in region k. The full model is given by

$$\begin{aligned} I^{SB}_{i,t+1} &= \alpha + (\beta_1 * RM_{k,t+1}) + (\beta_2 * T10_t) + (\beta_3 * EFF_i) + (\beta_4 * SIZE_i) + (\beta_5 * TOTCAP_{i,t}) \\ &\quad + (\beta_6 * SPRDSD_{ijk,t}) + (\beta_7 * REGUNCERT_{s,t}). \end{aligned}$$

The dependent variable $I^{SB}_{i,t+1}$ is an indicator which is equal to zero if generator i was operating both in year t and in year $t+1$, and equal to one if generator i was operating in year t and shutdown in year $t+1$. $RM_{k,t+1}$ is the projected reserve margin for region k for year $t+1$. $T10_t$ is the ten year treasury bond rate for year t. EFF_i is the efficiency of generator i. $SIZE_i$ is the capacity of generator i. $TOTCAP_{i,t}$ is the year t total capacity for the firm which owns generator i. $SPRDSD_{ijk,t}$ is the standard deviation of year t spark spread for generator i which burns fuel j and is located in region k. $REGUNCERT_{s,t}$ is an indicator variable which takes a value of one if there is regulatory uncertainty in state s (in which generator i resides) and year t, and, a value of zero otherwise. The table presents the average marginal effects $\left(\partial Prob(I^{SB}=1)/\partial x\right)$ of each independent (x) variable. For the indicator variable $REGUNCERT$, the table presents the change in the probability of a shutdown when the variable changes from zero to one. ***indicates significance at the 1% level, **at the 5% level, and *at the 10% level. Each regression has 6,515 observations.

RM	0.252***							0.235***
$T10$		-0.902***						0.799**
EFF			-0.064**					-0.047*
$SIZE$				-0.133**				-0.052
$TOTCAP$					-1.718***			-1.416***
$SPRDSD$						-1.016***		-0.609**
$REGUNCERT$							-0.014***	-0.012***
pseudo-R^2	14.3%	1.2%	0.7%	1.3%	4.1%	6.0%	4.0%	22.6%
Log-likelihood	-355.8	-409.9	-412.0	-409.8	-398.1	-390.3	-398.4	-321.0
AIC	715.6	823.8	828.0	823.7	800.1	784.5	800.9	658.1
BIC	729.2	837.4	841.6	837.2	813.7	798.1	814.5	712.5

Table 7: Startup and Abandonment: Univariate Statistics

Conditional on a generator being shutdown in year t, the table presents statistics for macroeconomic variables, firm-specific variables, generator-specific variables, and real options variables (i.e., measures of uncertainty) for generators which remained shutdown (SB) in year $t+1$, which started up (moved to operating, OP) in year $t+1$, and those which were abandoned (retired, RE) in year $t+1$. For startup and abandonment, the **delta** column shows the difference from the the generators which remained on standby.

Type	**Variable**	**SB**	**OP**	**delta**	**RE**	**delta**
Macro	Reserve Margin (%)	18.8%	16.4%	2.4%***	27.0%	-8.2%***
	Interest Rate (%)	4.78%	5.13%	-0.35%***	4.51%	0.27%***
Firm	Total Capacity (MW)	2,686	2,335	351	8,982	-6,296***
	Total Number of generators	27.5	25.7	1.8	83.9	-56.4***
Generator	Age (years)	23.8	21.9	1.9*	31.0	-7.2***
	Efficiency (%)	23.2%	24.2%	-1.0%***	20.7%	2.5%***
	Size (MW)	31.6	46.6	-15.0***	11.9	19.8***
	Time Shutdown (years)	2.55	1.16	1.39***	2.55	0.00
Real Options	Spark Spread Stdev ($/MWh)	$32.27	$36.10	-$3.83***	$23.39	$8.88***
	Regulatory Uncertainty Dummy	0.075	0.043	0.031*	0.026	0.049**
NOBS		1,312	184		78	

Table 8: Startup And Abandon Multinomial Logit Estimation Results

Consider generator i which burns fuel j and is located in region k. The full model is given by

$$\begin{aligned} I_{i,t+1}^{OPRE} &= \alpha + (\beta_1 * RM_{k,t+1}) + (\beta_2 * T10_t) + (\beta_3 * EFF_i) + (\beta_4 * SIZE_i) + (\beta_5 * TOTCAP_{i,t}) \\ &\quad + (\beta_6 * SBTIME_{i,t}) + (\beta_7 * SPRDSD_{ijk,t}) + (\beta_8 * REGUNCERT_{s,t}). \end{aligned}$$

The dependent variable $I_{i,t+1}^{OPRE}$ is a discrete variable which is equal to zero if generator i was on standby in year t and operating in year $t+1$, equal to one if generator i was on standby both in year t and in year $t+1$, equal to two if generator i was on standby in year t and retired in year $t+1$. $RM_{k,t+1}$ is the projected reserve margin for region k for year $t+1$. $T10_t$ is the ten year treasury bond rate for year t. EFF_i is the efficiency of generator i. $SIZE_i$ is the capacity of generator i. $TOTCAP_{i,t}$ is the year t total capacity for the firm which owns generator i. $SBTIME_{i,t}$ is the length of time, in years, that generator i has been shutdown as of year t. $SPRDSD_{ijk,t}$ is the standard deviation of year t spark spread for generator i which burns fuel j and is located in region k. $REGUNCERT_{s,t}$ is an indicator variable which takes a value of one if there is regulatory uncertainty in state s (in which generator i resides) and year t, and, a value of zero otherwise. The table presents the average marginal effects $\left(\partial Prob(I^{SB}=1)/\partial x\right)$ of each independent (x) variable. For the indicator variable $REGUNCERT$, the table presents the change in the probability of a startup when the variable changes from zero to one. ***indicates significance at the 1% level, **at the 5% level, and *at the 10% level. Each regression has 1,574 observations.

Startup	RM	-0.835***								-0.757***
	$T10$		7.764***							-2.145
	EFF			0.542**						0.121
	$SIZE$				1.117***					0.947***
	$TOTCAP$					-4.064*				-6.124**
	$SBTIME$						-0.039***			-0.035***
	$SPRDSD$							1.725***		0.613*
	$REGUNCERT$								-0.046*	-0.064***
Abandon	RM	1.057***								0.242*
	$T10$		-4.469***							-1.237
	EFF			-0.588***						-0.004
	$SIZE$				-2.664***					-4.363***
	$TOTCAP$					10.965***				12.322***
	$SBTIME$						0.002			0.013***
	$SPRDSD$							-3.229***		-1.367***
	$REGUNCERT$								-0.033***	0.010
	pseudo-R^2	9.6%	3.6%	1.9%	4.4%	7.8%	4.6%	2.7%	0.3%	29.0%
	Log-likelihood	-784.5	-836.9	-852.0	-830.3	-800.8	-828.7	-845.0	-865.3	-616.1
	AIC	1,577	1,682	1,712	1,669	1,609	1,665	1,698	1,739	1,268
	BIC	1,599	1,703	1,734	1,690	1,631	1,687	1,719	1,760	1,365

Figure 1: Shutdown Probability

The top panel presents the probability of shutting down an operating generator as a function for reserve margin for the cases of regulatory uncertainty (blue circles) and no uncertainty (red squares). The bottom panel presents the probability of shutting down an operating generator as a function for reserve margin for three values of spark spread volatility - \$10/MWh (blue circles), \$30/MWh (red squares), and \$100/MWh (green triangles).

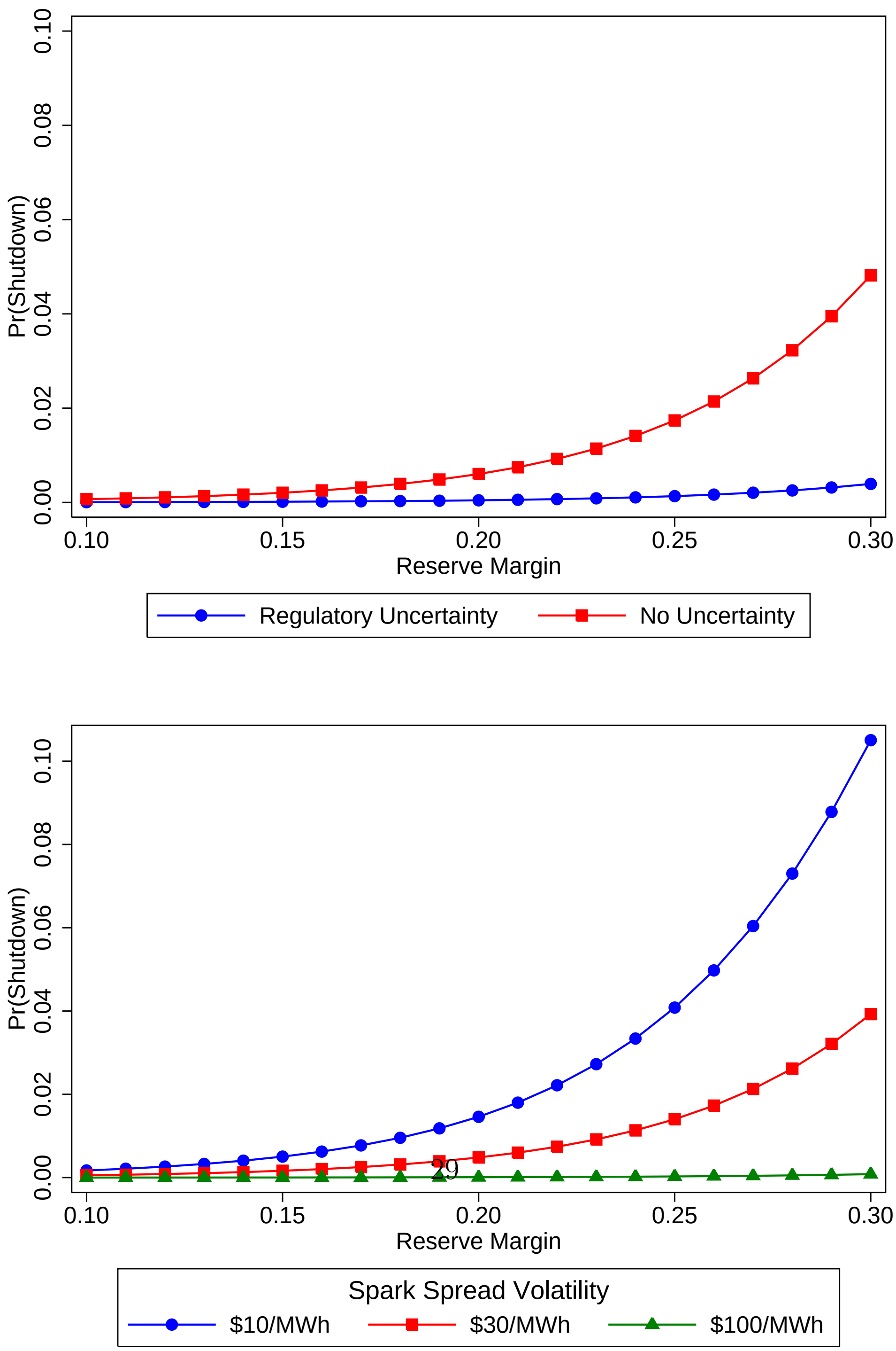
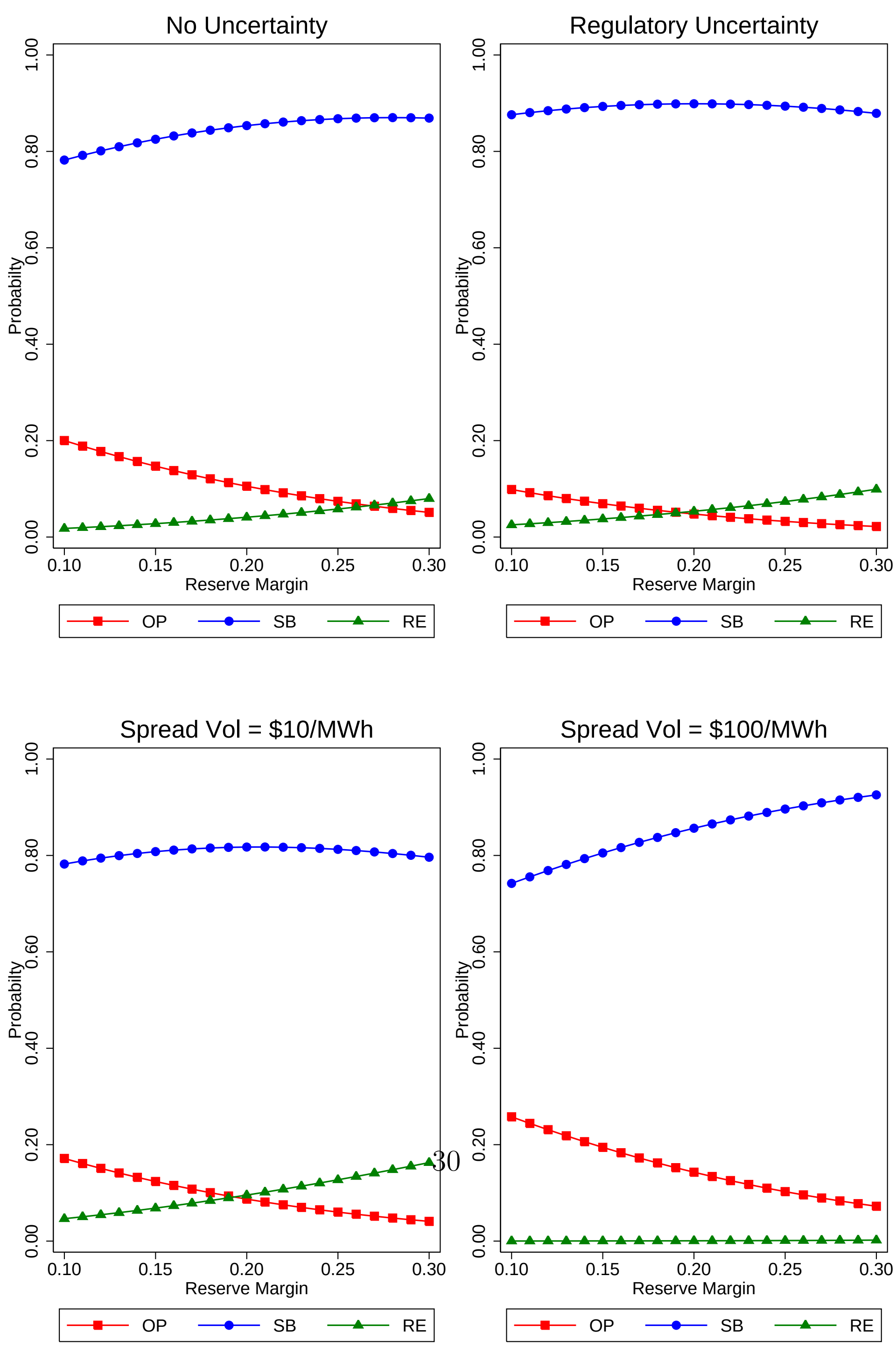


Figure 2: Startup and Abandonment Probability

For generators which were previously shutdown, the figure present the probability of startup (OP, red squares), remaining on standby (SB, blue circles), and abandonment (RE, green triangles) as a function of reserve margin. The top panel shows the probabilities for no regulatory uncertainty (left) and regulatory uncertainty (right). The bottom panel shows the probabilities for low spark spread volatility of ($10/MWh, left) and high spark spread volatility ($100/MWh right).



Appendix A. Heat Rate Data

Heat rate data are available for 943 of the 1,121 generators in our sample. In order to estimate the heat rates of the remaining 178 generators, we calculate mean heat rates by size and in-service year. The heat rate for a combustion turbine varies (1) inversely with the size of the generator (bigger machines are more efficient), and (2) directly with the age of the generator (newer machines are much more efficient). We classify generators into size and age categories (five of each) and then calculate the average heat rate in each age-size category based upon the heat rates available from CEMS and Form 860. We then use these average heat rates for other generators in these size-age categories.

For example, heat rate data is available for 318 generators which went into service in the 1970s and with capacity less than 50MW. The average heat rate for these 318 generators is 16.055 MMBtu/MWh. There are 16 generators which fall into the same size-age category and for which no heat rate data are available. For those 16 generators we assign the heat rate to be 16.055 MMBtu/MWh.

Heat rate data is available for 26 generators which went into service in the 2000s and with capacity in the 100-150 MW range. The mean heat rate for these 26 generators is 11.880 MMBtu/MWh. There are 5 generators which fall into the same size-age category and for which no heat rate data are available. For those 5 generators we assign the heat rate to be 11.880 MMBtu/MWh. And so forth and so on.

Appendix B. Startup and Shutdown Costs

Most of the problems encountered in restarting a generator are associated with the control system, i.e., instrumentation, electronic controls, and wiring. In general these systems do not vary greatly with the size of the generator in question. Mechanical issues involved in shutdown and restart are primarily concerned with corrosion. Core preservation requires layup chemicals.[28]

Restarting a generator begins with checking the control loops. Maintenance personnel attempt to "shoot-the-loop", i.e., to check that each control loop is functioning and, if not, to determine where the problem lies. It is common for systems that were in perfect working order at the time the generator was shutdown to fail when restart is attempted.

The costs to restart a generator also can vary with corporate culture. Oftentimes maintenance of shutdown generators has a lower priority than maintaining operating generators. A willingness to spend money to maintain these systems while the generator is shutdown greatly reduces the one time cost associated with the actual restart. However, management may not perceive that spending money on a generator which is not currently operating is a wise investment. The unfortunate (for our purposes) conclusion is that two generators which are the same size, same age, and located in the same region can have very different shutdown and startup costs depending on managerial priorities.

In summary, there is no simple way to estimate the costs associated with shutting down and restarting a generator based strictly upon the data available from EIA. Each generator is unique and each firm is unique.

As discussed in the main text, we focus on simple cycle gas turbines only, thereby eliminating variation across technology types. The control system issues discussed above should not vary much with the capacity of the generator.

[28]For example, the introduction of nitrogen can prevent oxygen from coming into contact with the core and causing corrosion.