Keeping the Lights On Until the Regulator Makes Up His Mind![*]

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ABSTRACT

The purpose of this paper is to examine empirically the real options to shutdown, startup, and abandon existing production assets using detailed information for 1,121 individual power plants for the period 2001–2009, a total of 8,189 plant-year observations. We find strong evidence of real options effects. We find that uncertainty about the outcome of ongoing deregulation in retail electricity markets (i) decreases the probability of shutting down operating plants, and, (ii) decreases the probability of starting up plants which were previously shutdown.

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I. Introduction

Do managers take account of real options effects when making capital budgeting decisions? Survey results reported in the literature suggest that, for the most part, the answer is no.

Graham and Harvey (2001) report that only 26.6% of survey respondents "always or almost always" incorporate real options into project evaluation. Triantis (2005) cites surveys of CFOs and senior executives which find that 10-15% and 9%, respectively, use real options techniques. According to McDonald (2006), less than 25% of firms use the real options approach to capital budgeting. Block (2007) surveys *Fortune* 1000 companies and finds that 14.3% were using real options techiques. Baker, Dutta, and Saadi (2011) survey Canadian firms and find that only 16.8% report that they use real options for capital budgeting, ranking it last among nine capital budgeting techniques. They conclude by saying (p.27), "More than 30 years after the term was coined, real options have yet to be adopted by most companies as a tool for strategic decision making."

Even if managers do not make explicit use of real options techniques, McDonald (2000) suggests they might utilize "rules of thumb" which account for uncertainty and allow for optimal or near optimal decisions. Kellogg (2010) finds that oil well drilling firms do respond to changes in price volatility despite the fact that (p.32) " ... it seems unlikely that they are formally solving Bellman equations." He suggests that these firms have decision heuristics which approximate real options decision making processes.

The purpose of this paper is to test for real options effects in the decisions to shutdown, startup, and abandon existing production assets, which we refer to collectively as status changes. We conduct our tests using detailed information for 1,121 individual power plants. To the best of our knowledge, the data are unique in scope and level of detail. We provide strong evidence that decision makers take account of cash flow uncertainty and regulatory uncertainty when making shutdown, startup, and abandonment decisions.

The difference between the market values of electricity and fuel is referred to as the *spark spread*. A power plant comprises a series of call options written on the spark spread. An increase in spark spread volatility therefore increases the option value of the plant. We show that an increase in spark spread volatility (i) decreases the probability of shutting down an operating plant, (ii) increases the probability of starting up a plant which was previously shutdown, and, (iii) decreases the probability of abandoning a plant which was previously shutdown.

We add to the recent stream of literature which focuses on the effects of regulatory uncertainty on the managerial decisions.[3] We find that during times of regulatory uncertainty plants which are operating are less likely to be shutdown and plants which were previously shutdown are less likely to startup. Under traditional regulation, retail customers are captive. Retail deregulation allows customers to choose their electricity supplier. The advent of retail deregulation has the potential to significantly change the demand for electricity faced by any individual supplier. Uncertainty about the outcome of deregulation means that owners are unsure about the future profitability of their plants. Plant owners therefore rationally delay the decision to shutdown an operating plant, and the decision to startup a plant which was previously shutdown, until the outcome of the deregulation process is more certain.

We find no evidence that regulatory uncertainty affects abandonment decisions. Abandoning a plant which was previously shutdown has little effect on the cash flows of the firm because the plant is "out-of-the-game" already.

The remainder of the article is structured as follows. Section II provides a review of existing literature and serves to motivate our empirical exercise. Section III details the data. In Section IV we define shutdown, startup, and abandonment in our sample. In Sections V and VI we present the empirical results. Section VII concludes.

[3]For example Julio and Yook (2012) studies the effects of political uncertainty on corporate investment. Billingsley and Ullrich (2012) finds that regulatory uncertainty in electricity markets reduces capital investment.

II. Literature Review

The theory of real options predicts that, in the face of irreversible switching costs and uncertainty in cash flows, major changes in assets are subject to hysteresis, and can be structured as options. For example, the opportunity to invest in, shutdown (or mothball), restart, or abandon a production asset can be cast as call and put options on the present value of the cash flows of the asset.

Robichek and Horne (1967) recognize that the "possibility of future abandonment" is an important part of the value of any potential project and that it must be accounted for in the capital budgeting process.[4] McDonald and Siegel (1985) develop a methodology for valuing risky investments when the firm has the option to shutdown the project after it has been constructed. They introduce uncertainty in output prices and input costs. Brennan and Schwartz (1985) specialize a real options model for the case of a commodity mine and study optimal policies for shutting down an operating mine.

Empirical studies on real options include Quigg (1993), who uses data on land transactions to show that a real options model has some explanatory power for market prices, over and above net present value. Berger, Ofek, and Swary (1996) examine empirically the abandonment option of the firm as a whole and find that the market value of the firm is increasing in firm exit value. Bulan, Mayer, and Somerville (2009) investigate condominium development and find that increased volatility reduces probability of investment, and that a real options model explains the data better than a model of risk aversion. Kellogg (2010) finds that Texas oil companies reduce their drilling activity when volatility rises, and that the magnitude of this change is consistent with real options theory.

Moel and Tufano (2002) evaluate empirically the predictions of the Brennan and Schwartz (1985) model by examining the shutdown and startup decisions for 285 gold mine properties for the 1988-1997 time period. They find that a real options model describes well the empirical data. Our work differs from that of Moel and Tufano (2002) in important ways. First, we focus directly on status changes. Second, we

[4] In a comment to the original Robichek and Horne (1967) article Dyl and Long (1969) provide a modification which Robichek and Horne (1969) subsequently accept as correct.

include a measure of regulatory uncertainty. Third, we also examine the option to abandon a plant. Finally, our dataset is more detailed and has approximately four times as many observations as the data used by Moel and Tufano (2002).

III. Data

In this section we describe the sample data in detail. The 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 I presents summary statistics for the plant-specific variables in our sample, while Table II 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 power plant in the United States, both existing and planned. We consider plants 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.[5] The choice of areas and sample period is driven by (i) the availability of electricity price data and (ii) significant changes in Form 860 beginning in 2001. We focus on "peaking" plants as these should be more subject to the factors expected to influence shutdown, startup, and abandonment decisions.[6] The final data set contains 8,189 plant-year observations on 1,121 individual plants.

[5]Specifically, we include plants 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.

[6]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 plants, operate more-or-less continuously for the duration of their useful lives. Also, fuel prices for baseload technologies are very low and stable.

A. Plant Efficiency

The efficiency of a power plant is measured by its *heat rate*. The heat rate of plant 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 CEMS (Continuous Emissions Monitoring Systems) data from the U.S. Environmental Protection Agency.[7] CEMS data is available for 631 of the 1,121 plants in our sample. Heat rate data were included in Form 860 for 1990-1995. These data are available for 312 plants for which no CEMS data is available. Heat rates for the remaining 178 plants are estimated based on the age and size of the plant. Details are in Appendix A.

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. The two are related by a scale factor. In particular, there are 3.41275 $MMBtu$ in one MWh. We can thus convert a plant's heat rate into a dimensionless conversion efficiency as

$$EFF_i = \frac{3.41275}{HR_i} * 100\% \tag{1}$$

where EFF_i is the conversion efficiency of plant i which has heat rate HR_i. For example, a plant with a heat rate of 10 $MMBtu/MWh$ has a conversion efficiency of 34.1%. Summary statistics for the age (to the nearest year), size (in megawatts, MW), and efficiency (in %) are presented in Table I.[8]

[7] See http://camddataandmaps.epa.gov/gdm/index.cfm?fuseaction=prepackaged.select.

[8] Ages are calculated based upon the first year a plant appears in the database. The efficiency reported in the tables and used in the regressions is literally $\frac{energy\,out}{energy\,in}$. Kovenock and Phillips (1997) emphasize the importance of controlling for plant efficiency and industry capacity utilization in investment and abandonment decisions.

B. Spark Spread Volatility

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

$$SPRD_{ijk,n} = P^{elec}_{k,n} - HR_i * P^{fuel}_{j,n}, \tag{2}$$

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

$$SPRDSD_{ijk,t} = STDEV^{T}_{n=1}\left(SPRD_{ijk,n}\right), \tag{3}$$

where T is the number of days in year t.

C. Supply and Demand Data

Because electricity cannot be stored, available supply (i.e., capacity) must always exceed contemporaneous demand in order to prevent blackouts.[10] We measure supply adequacy by reserve margin. Reserve margin for region k and year t ($RM_{k,t}$) is defined to be

$$RM_{k,t} \equiv (C_{k,t} - D_{k,t})/D_{k,t}, \tag{4}$$

[9] Consistent with our focus on peaking plants, 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.

[10] Triantis and Hodder (1990) develop an analytical model to value flexibility in the production process. In particular, they relax the assumption of perfect competition and also allow for a capacity constraint.

where $C_{k,t}$ is the year t capacity in region k and $D_{k,t}$ is the year t demand in region k, both measured in MW. The raw data come NERC's 2009 Electricity Supply and Demand (ES&D) database. For planning purposes, target reserve margin values range from 15% to 20%. Table II 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%, repsectively.

Projected reserve margin serves as our proxy for expected future profitability. Lack of storability implies that, when demand approaches available supply, electricity prices increase at an increasing rate.[11] The lower is the reserve margin, the less excess capacity there is in the system, and the higher are wholesale electricity prices. Thus projected reserve margin acts as an (inverse) proxy for expected future profitability of the plant. Low reserve margins imply high future profitability and vise versa.[12]

C.1. Time Sequence of Data Availability

Form 860 must be filed by mid-February each year. We take the data reported, for example, in the 2005 Form 860 to be effective as of the end of calendar year 2004. In the regressions which follow we use only those data which were available as of the end of 2004 in order to predict a status change (shutdown, startup, or abandonment) during the next year, i.e., by the end of 2005. Any such change would show up in the 2006 Form 860.

At the time the 2005 Form 860 was filed, the 2004 ES&D database was the most recent available. The 2004 ES&D database contains actual supply and demand data for 2003 and projections for 2004-2013. In trying to predict whether a plant has a status change in 2005, we use the projected 2005 reserve margin from the 2004 ES&D database.

[11] See, for example, Bessembinder and Lemmon (2002), Mount, Ning, and Cai (2006), and Ullrich (2012).

[12] There are other channels through which plants can earn income. Spinning reserve 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 trips offline. The plants 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 this year (2012) NSR has not been compensated in PJM.

D. Regulatory Uncertainty

Before the advent of retail competition in the U.S., customers located in a particular utility's service territory were captive customers of that utility. The utility was required to maintain enough resources to meet the demand of its captive customers. Deregulation of retail electricity markets allows customers to choose electricity suppliers. The prospect of retail competition leaves utilities in the position of possibly losing (or gaining) a significant portion of existing demand. If the utility's neighbors have lower cost generation available, and the utility loses some of its existing demand when retail competition is implemented, then a plant which was economic when used to meet native demand in the regulated world might not be needed under retail competition. Also, retail competition might mean that a plant which would not have run under regulation will be profitable again.

Deregulation of retail electricity markets in the U.S. is taking place at the state level. The EIA publishes a descriptive summary of state-level deregulation. This information, supplemented by state utility commission information, allows the construction of a state-level retail competition index.[13] 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 competition in the retail market. Our interest in is uncertainty. When the competition index takes a value of two, there is uncertainty about whether the state will implement retail competition. When the index takes a value of three, there is uncertainty about the form retail competition will ultimately take. We define a regulatory uncertainty indicator variable ($REGUNCERT$) which takes a

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

value of one when the competition index above is equal to either two or three, and which takes a value of zero otherwise.

Consistent with real options theory, we expect firms to be less likely to make changes in the status of existing generators when there is uncertainty about the outcome of retail deregulation. Approximately 20.5%[14] of our total samples observations occur during a period of regulatory uncertainty. As detailed in Tables V and VII, there are a total of 338 instances of shutdowns, startups, and abandonments in our sample. Of these, only 11, or 3.25%, take place during periods of regulatory uncertainty.

E. Portfolio Effects

The decision to shutdown, startup, and/or abandon a plant 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 plant, 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 plants. We use two measures of firm size, the total capacity owned by the firm and the total number of plants owned by the firm. The summary statistics in Table II show that there is a great deal of variation in the size of the firms in our sample.

IV. Status Change Definitions

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

- OP - operating,
- SB - standby, and,

[14] In Table II we report that the mean value of the regulatory uncertainty variable is 0.217. In the calculation of the statistics in Table II we use only one observation per state-year, not every observation.

- RE - retired.

Details are found in Appendix C.

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

Consider a plant which is operating (status OP) in the current year. Next year, the plant may either continue to operate (remain in status OP) or move to standby (SB).[15] We define a “shutdown” to be movement from status OP in year t to status SB in year $t+1$.[16] Table III documents the occurence of shutdowns by year in our sample. For example, of the 832 plants which were operating in 2004, 820 continued to operate in 2005 while 12 were shutdown. For the full sample there are a total of 76 instances of shutdown versus 6,539 instances of a operating plant remaining in operating mode.

Consider a plant which was previously shutdown, i.e., a plant which is on standby (SB) in the current year. Next year the plant 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 IV documents occurrences of these alternatives by year in our sample. For example, of the 188 plants 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.

[15] While it is possible to move directly from status OP (operating) to status RE (retired), such moves are rare and are not driven purely by spark spread economics.

[16] It is conceivable that the status of a plant 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.

V. Shutdown

In this section we examine the decision to shutdown an operating plant, i.e., to move from status code OP to status code SB. Table V presents comparative univariate statistics for plants which were shutdown and those which continued to operate. The descriptive variables are divided into four categories - macroeconomic, firm-specific, plant-specific, and real options, i.e., measures of uncertainty. The last column presents differences. All of these differences are significant at the 5% or 1% level.

Beginning with the macro variables, plants tend to be shutdown when projected reserve margins are high. High reserve margins imply low future profitability. Plants 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 plant will shutdown. The univariate statistics in Table V suggest exactly the opposite - plants tend to shutdown when interest rates are lower. However, reserve margin and interest rates are negatively correlated.[17] We believe that, when considered in isolation, interest rates are simply proxying for reserve margin. The multivariate analysis below confirms this conjecture. When we control for reserve margin, the 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 plants owned by the firm. Table V indicates that firms which shutdown plants tend to be much smaller than firms which continue to operate existing plants, as measured both by total capacity owned and by total number of plants. We think there are at least two potential explanations for this effect. First, smaller firms have fewer opportunities to subsidize less profitable plants. Second, and perhaps more important, many of the small firms in our sample are firms whose primary business is not electricity generation.[18]

[17] 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. In PJM, where the majority of status changes take place, the correlation is -0.60.

[18] Of the 212 total firms in the sample, 27 own only one plant.

These firms do not have the same level of in-house maintenance expertise as do firms whose primary business is electricity generation. When the plants owned by these firms age and become relatively less cost effective, it is more costly for these firms to undertake the maintenance required to keep the plant operational, hence they are more likely to shutdown the plant.

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

Spark spread 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, the table shows that shutdowns are more likely when (i) spark spread volatility is lower, and, (ii) there is less uncertainty about the outcome of retail deregulation. The differences are large.

On average spark spread volatility for plants which shutdown is 31% less than spark spread volatility for plants which continue to operate. The regulatory uncertainty data is even more striking. Of the total 8,189 observations, 20.5% occur during times of regulatory uncertainty. Table V 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. In the next subsection we turn to a multivariate analysis.

A. Binary Logit Regression

Consider plant i which burns fuel j and is located in region k. We begin our multivariate analysis using a binary logit specification, as follows.[19]

$$\begin{aligned} I^{SB}_{i,t+1} &= \alpha + (\beta_1 * RM_{k,t+1}) + (\beta_2 * T10_t) + (\beta_3 * EFF_i) + (\beta_4 * SIZE_i) + (\beta_5 * TOTCAP_i) \\ &\quad + (\beta_6 * SPRDSD_{ijk,t}) + (\beta_7 * REGUNCERT_t) + \varepsilon, \end{aligned} \tag{5}$$

[19]We do not include AGE as a regressor. Because older plants tend to be less efficient, AGE and EFF are highly collinear. Similarly, the total capacity owned by a firm ($TOTCAP$) and the total number of plants ($TOTPLT$) are highly collinear. We choose to omit $TOTPLT$ in the regression specification.

where

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

$RM_{k,t+1}$ 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 plant i,

$SIZE_i$ is the capacity of plant i,

$TOTCAP_i$ is the total capacity owned by the firm which owns plant i,

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

$REGUNCERT_t$ is an indicator variable which takes a value of one in years in which the outcome of retail deregulation is uncertain and a value of zero otherwise.

The first five regressors, RM through $TOTCAP$ should matter in both a traditional discounted cash flow analysis and a real options framework. The last two regressors, $SPRDSD$ and $REGUNCERT$, are measures of uncertainty and should matter if the owners of plants consider real options effects when making shutdown decisions. Table VI presents the results. 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. We begin by including each independent variable separately. Each coefficient is significant and the signs are consistent with the summary statistics in Table V.

B. Individual Regressions

Analyzing each variable separately allows us to get a feel for which of the variables 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 plants are more likely to be shutdown when there is a greater excess of existing capacity. As discussed above, higher reserve margins imply lower wholesale electricity prices and therefore less valuable plants. Plants tend to shutdown when expected future profitability is low.

The coefficients for the real options variables *SPRDSD* and *REGUNCERT* are negative and significant. Increases in spark spread volatility and regulatory uncertainty each reduce the probability of shutting down an operating plant.

C. Full Regression

The last column of Table VI 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.[20] Most importantly, the coefficients on *SPRDSD* and *REGUNCERT* remain negative and significant. Consistent with our priors, increases in either spark spread volatility or regulatory uncertainty decrease the probability of shutting down an operating plant 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 VI. 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

[20]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.

profitability), the probability of shutting down an operating plant 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 plant 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 plant is small for any value of reserve margin. Uncertainty in the regulatory environment translates in to uncertainty about plant profitability, hence plant owners are more hesitant to shutdown operating plants.

The bottom panel of Figure 1 presents the probability of shutting down an operating plant 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).[21] When reserve margin is low (future profitability is high), the probability of shutting down an operating plant is small, irrespective of spark spread volatility. In this case the spark spread options which comprise the plant are effectively in-the-money and optionality constitutes a relatively small part of the plant's value, so spark spread volatility is less important to the shutdown decision.

When reserve margin is high (future profitability is low), the spark spread options which comprise the plant are out-of-the-money, optionality is the main source of the plant's value, and spark spread volatility is very important to the shutdown decision. When spark spread volatility is high, the option value of the plant 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 plant are both out-of-the-money and the volatility of the underlying asset (the spark spread) is low, rendering the options nearly worthless. As a result, the probability of shutting down an operating plant increases in reserve margin. As Table VI and Figure 1 make clear, these effects are both statistically and economically significant.

[21] 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.

VI. Startup and Abandonment

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

A. Startup

Consider first plants which startup. Plants 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 VII 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 VII also shows that firms which restart plants are not significantly different in size than firms for which plants remain shutdown, as measured by either total capacity or total number of plants.

Plants which startup are on average younger, more efficient, and larger than plants which remain shutdown. According to the theory, important determinants of the decision to shutdown and/or startup a plant are the cost involved doing so, both the one time costs and continuing costs. We proxy for startup costs by calculating the amount of time (in years) that a plant has been shutdown. The assumption is that a plant which has been shutdown for a long period of time has higher startup costs than an otherwise similar plant which has been shutdown for a shorter length of time.[22] Plants which startup have been shutdown for a

[22] In general, the cost to shutdown a plant is small relative to the cost to restart a plant. The cost to restart varies with the level of maintenance performed while the plant is shutdown, 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. 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.

shorter period of time (1.16 years) that plants which remain shutdown (2.55 years) indicating that plants which startup have lower startup costs than plants which remain shutdown.

Turning to the real options variables, Table VII shows that plants which startup have higher spark spread volatility than plants which remain shutdown. Higher spark spread volatility means that the options which comprise the plant have significant option value which can be captured if the plant is operational, therefore increasing the probability of startup.

Table VII also shows that startups tend to occur when uncertainty about the outcome of retail deregulation is low. Of the 184 total instances of startup in our sample, only eight ($\frac{8}{184} = 0.031$) took place during a time of regulatory uncertainty.

B. Abandonment

Next consider plants which are abandoned. The last two columns of Table VII show that plants tend to be abandoned when projected reserve margins are high and expected future profitability therefore is low.

Firms which abandon plants tend to be much (three to four times) larger than those which do not. The size of the firm may well serve as a proxy for abandonment costs. A large electric utility which wants to build a new plant may have a very hard time locating and obtaining permits for a new site. A much less expensive and less time consuming alternative is to use an existing site. By abandoning an existing plant, the utility can free up space for the new plant. The abandonment cost in this case is positive, it looks like a salvage value.

Abandonments take place when spark spread volatility is low and when uncertainty about retail deregulation is low. Specifically, spark spread volatility for plants which are abandoned is 27.5% less than spark spread volatility for plants 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.

C. 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 allows us to consider the startup and abandonment decisions simultaneously.

$$\begin{aligned} I_{i,t+1}^{OPRE} &= \alpha + (\beta_1 * RM_{k,t+1}) + (\beta_2 * T10_t) + (\beta_3 * EFF_i) + (\beta_4 * SIZE_i) + (\beta_5 * TOTCAP_i) \\ &\quad + (\beta_6 * SBTIME_{i,t}) + (\beta_7 * SPRDSD_{ijk,t}) + (\beta_8 * REGUNCERT_t) + \varepsilon, \end{aligned} \tag{6}$$

where

$I_{i,t+1}^{OPRE}$ is an indicator which is equal to zero if plant i was on standby in year t and operating in year $t+1$, equal to one if plant i was on standby both in year t and in year $t+1$, equal to two if plant i was on standby in year t and retired in year $t+1$,

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

and all the other variables are as defined above. The results are presented in Table VIII.[23] 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.

C.1. Startup

The top panel of Table VIII presents regression results for startup from equation (6). 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

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

startup decision are expected future profitability (*RM*), plant size (*SIZE*), startup costs (*SBTIME*), and the regulatory environment (*REGUNCERT*). Startups are more likely when expected future profitability is higher, for larger plants, and when startup costs are lower. Regulatory uncertainty reduces the probability of starting up a plant which was previously shutdown.

In the individual startup regression the coefficient on spark spread volatility ($\beta_7 = 1.725$) is positive and strongly significant. Higher spark spread volatility increases the option value of the plant itself and therefore increases the probability of startup. However, in the overall regression, the coefficient on spark spread volatility ($\beta_7 = 0.613$) is reduced in magnitude from the individual regression and is no longer significant. We discuss this further in the **"Startup and Plant Size"** subsection below.

C.2. Abandonment

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

Importantly, the coefficient on spark spread volatility is negative and strongly significant in both the individual regression and the full regression. Higher spark spread volatility increases the option value of the plant in question and therefore decreases the probability of abandonment.

In the full model, regulatory uncertainty is not important for making the abandonment decision. Because plants which were previously shutdown are "out-of-the-game" already, abandoning the plant 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.

C.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. The figures are based upon the full regression (last column) in Table VIII.

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, regulatory uncertainty significantly reduces the probability of startup. 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 plant owners are uncertain about the outcome of retail deregulation and thus about potential gains or losses in retail customers, they delay the decision to restart plants which may otherwise have restarted.

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 shows that the probability of startup (red squares) increases with spark spread volatility.[24] As discussed above, this result is due to the option-like nature of a power plant. Higher spark spread volatility increases the option value of the plant and therefore increases the probability of startup.

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 plant 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 plant is high

[24] Even though the effect of spark spread volatility on startup probability is large (as demonstrated by the curves with the red squares in the lower left and right panels of Figure 2), it is not statistically significant.

and the probability of abandonment is small regardless of reserve margin. This effect is statistically and economically significant.

D. Startup and Plant Size

In the regression results for startup and abandonment in Table VIII the coefficient on plant size ($SIZE$) is strongly significant. Large plants are more likely to startup and less likely to be abandoned.[25] Figure 3 plots histograms of the distribution of plant size for plants which startup (top panel) and plants which are abandoned (bottom panel). The figure makes obvious that all of the plants which are abandoned (and most of the plants which are started up) are small, less than 25 MW.

We repeat the regression from equation (6) for small plants, with less than 25 MW capacity. In order to save space we do not report the results in a table. The fit of the overall regression (psuedo-$R^2 = 40.3\%$) is much better than the full sample regression (psuedo-$R^2 = 29.0\%$) reported in Table VIII. The coefficients on the real options variables are reduced in magnitude from the full sample regression. While regulatory uncertainty was signficant in the full sample regressions ($\beta_8 = -0.064$, significant at 1%), it is no longer significant when the regression is restricted to small plants. The implication is that regulatory uncertainty matters for startup decisions, but not for the smallest plants.

It is not possible to repeat the multinomial logit regression for large plants because all abandonments involve very small plants. Instead we perform binary logit regression for startup, similar to the full shutdown regression reported in Section V, with the sample limited to plants larger than 25 MW. In order to save space we do not report the results in a table. In contrast to the results presented in Table VIII, the coefficient on spark spread volatility is $\beta_7 = 2.455$ and significant at the 1% level. Spark spread volatility is important for startup decisions for all except the smallest plants.

[25] Recall from Table VII the average size for plants which startup is 46.6 MW, while the average size for plants which are abandoned is 11.9 MW.

VII. Conclusions

We examine the real options to shutdown, startup, and abandon existing power plants. We find strong evidence of real options effects. Consistent with the theory we find that an increase in spark spread volatility decreases the probability that an operating plant will be shutdown and decreases the probability that a plant which was previously shutdown will be abandoned. We also find that an increase in spark spread volatility increases the probability that a plant which was previously shutdown will be started up.

Regulatory uncertainty, specifically uncertainty about the outcome of deregulation in retail electricity markets, decreases the probability of shutting down plants which are operating and decreases the probability of starting up a plant which was previously shutdown. We find no evidence that regulatory uncertainty affects abandonment decisions.

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Table I
Plant Summary Statistics

The table presents summary statistics for the age (to the nearest year), size (megawatts, MW), and efficiency (%) of plants in the sample. The ages are calculated based upon the first year a plant 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 II
Macro, Real Options, and Firm Variables 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 III 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 plants 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 III
Shutdown: Transitions from OP to OP/SB by Year

Number of plants 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 IV
Startup and Abandonment: Transitions from SB to OP/SB/RE by Year

Number of plants 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 V
Shutdown: Univariate Statistics

Conditional on a plant operating in year t, the table presents statistics for macroeconomic variables, firm-specific variables, plant-specific variables, and real options variables (i.e., measures of uncertainty) for plants 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 Plants	56.5	28.4	28.2***
Plant	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 VI: Shutdown Binary Logit Estimation Results

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

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

The dependent variable $I^{SB}_{i,t+1}$ is an indicator which is equal to zero if plant i was operating both in year t and in year $t+1$, and equal to one if plant 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 plant i. $SIZE_i$ is the capacity of plant i. $TOTCAP_i$ is the total capacity for the firm which owns plant i. $SPRDSD_{ijk,t}$ is the standard deviation of year t spark spread for plant i which burns fuel j and is located in region k. $REGUNCERT_t$ is the year t retail competition index. The table presents the average marginal effects $\left(\partial Prob(I^{SB}=1)/\partial x\right)$ of each independent (x) variable. For the indicator variables ($REGST$ and $REGUNCERT$) 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, **indicates significance at the 5% level, and *indicates significance 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 VII
Startup and Abandonment: Univariate Statistics

Conditional on a plant being shutdown in year t, the table presents statistics for macroeconomic variables, firm-specific variables, plant-specific variables, and real options variables (i.e., measures of uncertainty) for plants 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 plants 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 Plants	27.5	25.7	1.8	83.9	-56.4***
Plant	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 VIII: Startup And Abandon Multinomial Logit Estimation Results

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

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

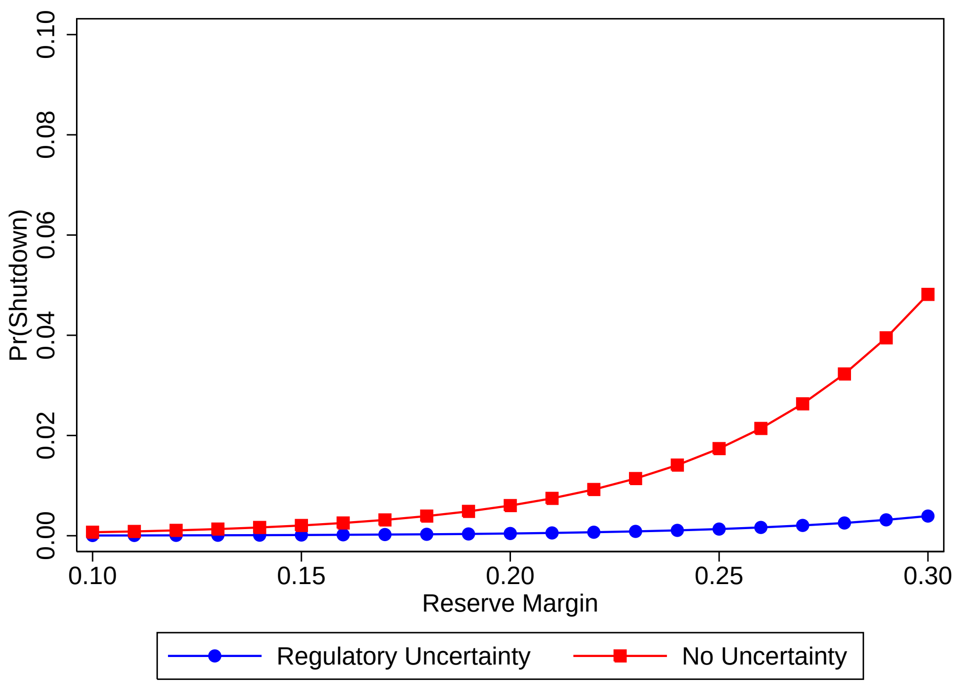
The dependent variable $I^{OPRE}_{i,t+1}$ is an indicator which is equal to zero if plant i was on standby in year t and operating in year $t+1$, equal to one if plant i was on standby both in year t and in year $t+1$, equal to two if plant i was on standby in year t and retired in year $t+1$. $RM_{k,t+1}$ 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 plant i. $SIZE_i$ is the capacity of plant i. $TOTCAP_i$ is the total capacity for the firm which owns plant i. $SBTIME_{i,t}$ is the length of time, in years, that plant i has been shutdown as of year t. $SPRDSD_{ijk,t}$ is the standard deviation of year t spark spread for plant i which burns fuel j and is located in region k. $REGUNCERT_t$ is the year t retail competition index. The table presents the average marginal effects $\left(\partial Prob(I^{SB}=1)/\partial x\right)$ of each independent (x) variable. For the indicator variables ($REGST$ and $REGUNCERT$) 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, **indicates significance at the 5% level, and *indicates significance 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 plant 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 plant 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).



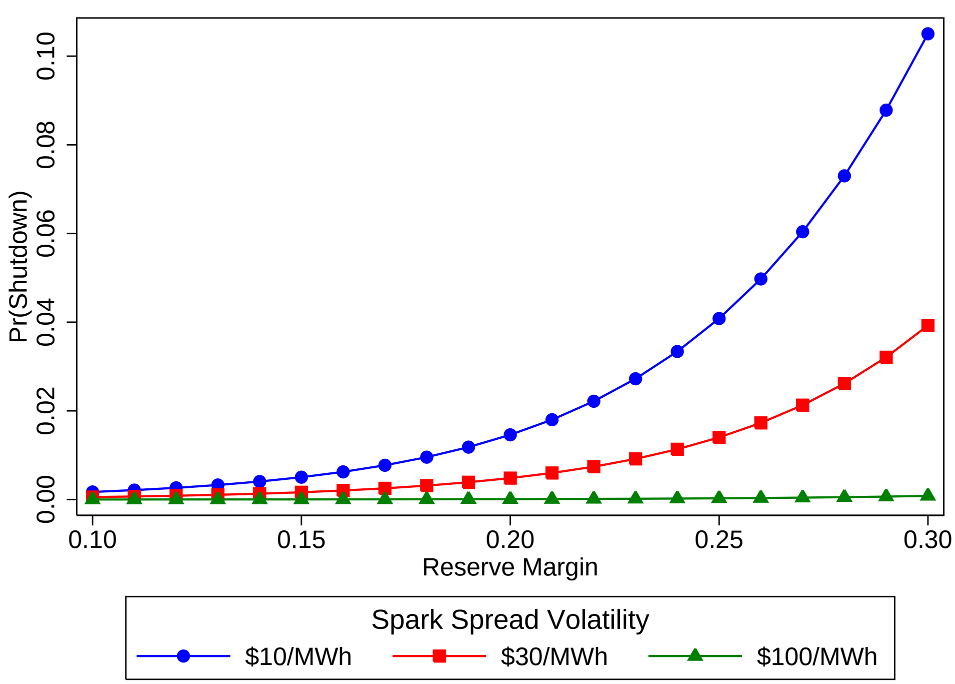


Figure 2

Startup and Abandonment Probability

For plants 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).

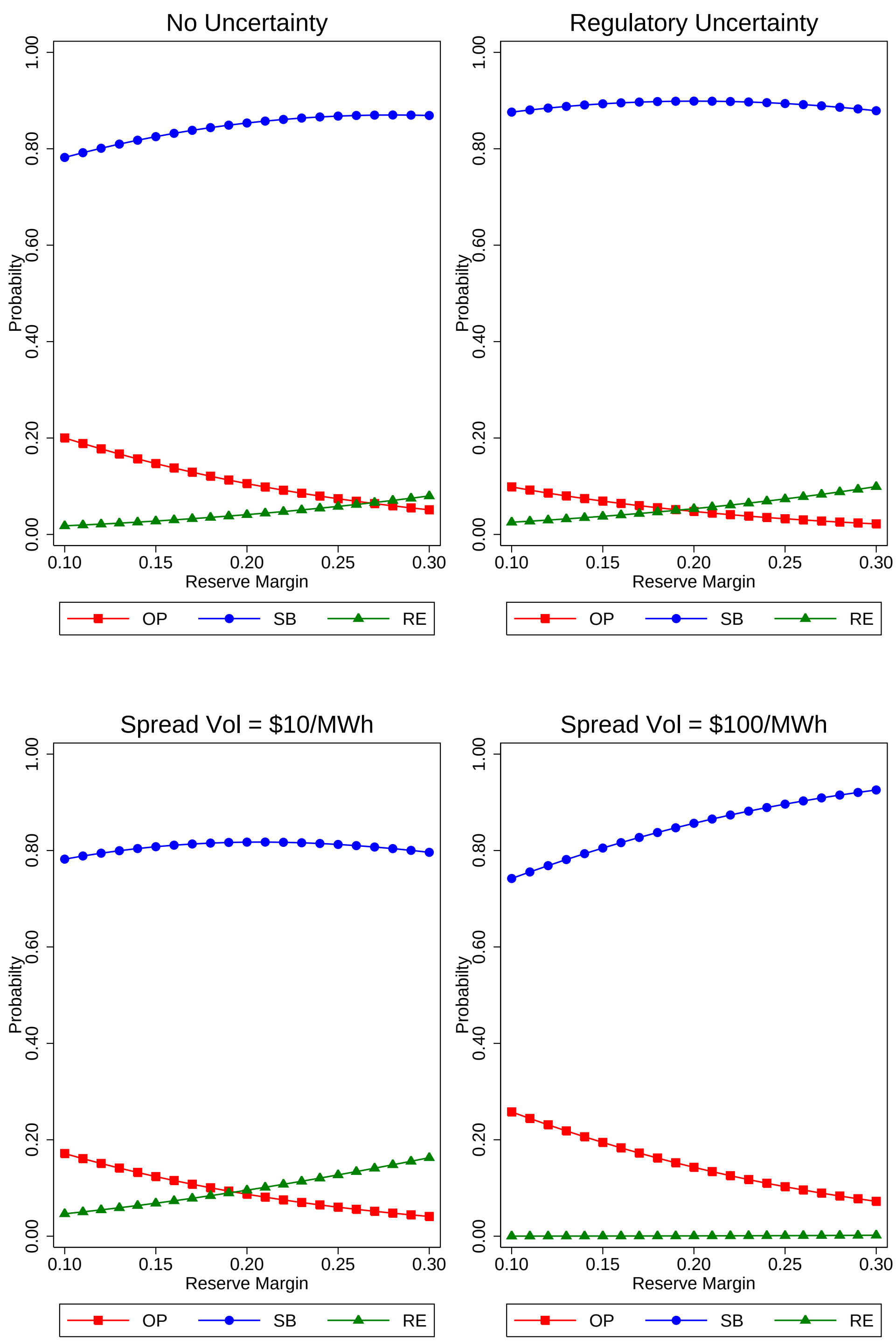
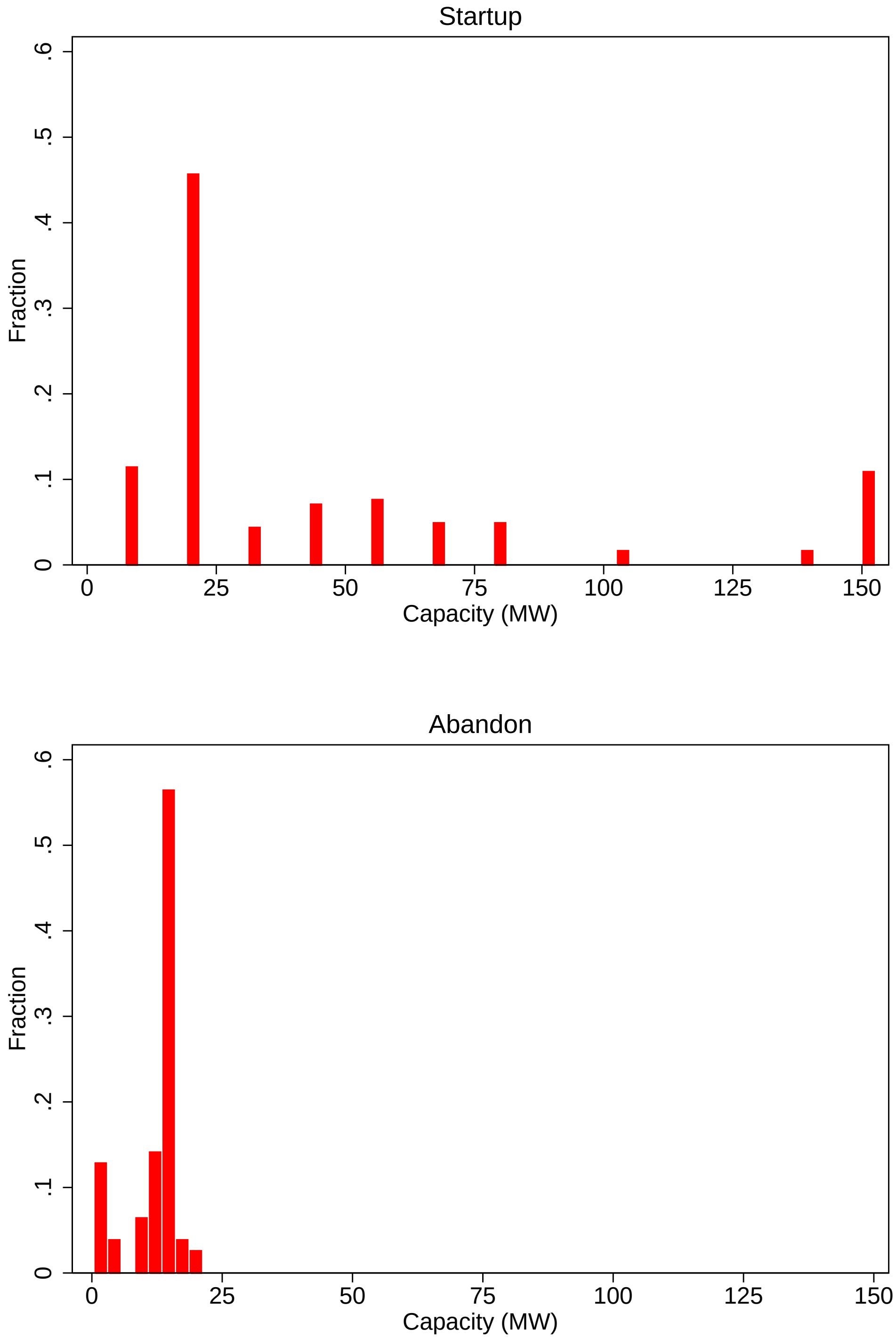


Figure 3

Histogram of Capacity for Startup and Abandonment

For plants which were previously shutdown, the figure present histograms of capacity. The top panel shows the distribution of capacity for plants which startup. The bottom shows the distribution of capacity for plants which are abandoned.



Appendix A. Heat Rate Data

Heat rate data is available for 943 of the 1,121 plants in our sample. In order to estimate the heat rates of the remaining 178 plants, 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 plant (bigger machines are more efficient), and (2) directly with the age of the plant (newer machines are much more efficient). We classify plants 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 plants in these size-age categories.

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

Heat rate data is available for 26 plants which went into service in the 2000s and with capacity in the 100-150 MW range. The mean heat rate for these 26 plants is 11.880 MMBtu/MWh. There are 5 plants which fall into the same size-age category and for which no heat rate data are available. For those 5 plants 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 plant 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 plant in question. Mechanical issues involved in shutdown and restart are primarily concerned with corrosion. Core preservation requires layup chemicals.[26]

Restarting a plant 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 plant was shutdown to fail when restart is attempted.

The costs to restart a plant also can vary with the corporate culture of the owner. Oftentimes maintenance of shutdown plants has a lower priority than maintaining operating plants. A willingness to spend money to maintain these systems while the plant is shutdown greatly reduces the one time cost associated with the actual restart. However, management may not perceive that spending money on a plant which is not currently operating is a wise investment.

The unfortunate (for our purposes) conclusion is that two plants which are the same size, same age, and located in the same region can have very different shutdown and startup costs depending on the priorities of the management team.

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

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

Appendix C. Status Codes SB and BU - Definitions and Changes

For every year, EIA provides variable definitions in a *Layout* file accompanying the EIA 860 data. Status code SB is not defined in the *Layout* file for the 2001 and 2002 years. However, the 2000 *Layout* file 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."

Beginning in 2003 SB is defined as

> "Standby - available for service but not normally used (has little or no generation during the year)."

Status code BU is available only for the 2004-2006 time period. For the 2004-2006 time period, the definition of SB is unchanged. BU is defined as

> "Backup - used for test purposes or emergency such as shortage to power to meet load requirements."

For the 2007-2009 time period, BU again disappears and SB is defined as

> "Standby/Backup - available for service but not normally used (has little or no generation during the year)."