# An Empirical Study of Sequential Investments with Time-To-Build

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Abstract
This paper presents an empirical study of the real options to postpone or cancel sequential investments in power plants with time-to-build. We find that utilities rather proceed with investments in smaller, less irreversible technologies when there is regulatory uncertainty. In addition we find that there is value in the flexibility to adjust production when prices are volatile and that increased volatility is an incentive to complete sequential investments in peak load power plants.

Project Thesis

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# 1 Introduction

It is possible to evaluate a real investment project as holding a call option on a dividend paying stock, and exercising the option is equivalent to paying the investment cost. As with financial options, increased uncertainty increases the incentive to delay the investment, and leads to an optimal investment threshold where project value exceeds costs by a positive amount (Majd and Pindyck, 1987). The traditional valuation approaches may lead to incorrect investment decision rules because they fail to account for irreversibility, timing and uncertainty over future rewards. Irreversibility means that investment costs are at least partially sunk. McDonald and Siegel (1986) show that even with moderate levels of uncertainty, the value of the opportunity cost of investing can be large, and an investment rule that ignores it will be grossly in error. Pindyck (1988) shows that, for moderate amounts of uncertainty, a firm's optimal capacity choice is much smaller than it would be if investments were reversible for marginal investment decisions. Several techniques for valuing real option projects have been developed and are provided extensively in textbooks such as Dixit and Pindyck (1994) and Trigeorgis (1996). Irreversibility, timing and uncertainty factors are characteristics of most real life investment decisions and are taken into account in real option analysis. Investment decisions appear to be more sensitive to volatility and uncertainty in the economic environment rather than taxes and interest rates (Dixit and Pindyck, 1994). Real option models therefore capture actual business conditions better than traditional models .

Another feature of real life investments is that they rarely occur instantaneously. Investment decisions are usually made sequentially over time and in a particular order. Peeters (1996) distinguishes between two types of gestation lags; construction- and delivery lags. Construction lags cause time-to-build while equipment is subject to delivery lags as a result of delays in ordering, installing or delivery. In this paper we do not separate the two types of lags, and use the expression time-to-build for the total lag. Projects usually have several milestones that have to be reached before one can proceed with the investment process. When some factors make it more valuable to invest at a later point in time, e.g. due to arrival of new information, a firm might depart from the original schedule. Investments in power plants are multistage projects. In the first stage the utility applies for regulatory approval for the plant. If permits are received the utility can begin construction and later decide if they want to start operating. At any point the project owners may decide to proceed as planned, postpone or cancel the project. These projects do not yield any cash returns until they are finalized (Majd and Pindyck, 1987). A sequential investment project is analogous to a compound option. Each stage completed gives the investing firm an option to start the next. One can therefore use principles from financial options when valuing these opportunities (Dixit and Pindyck, 1994).

Majd and Pindyck (1987) use option pricing techniques to derive a model for optimal decision rules for unregulated firms in sequential irreversible investments with time-to-build. They show that with moderate levels of uncertainty over the future value of the completed project, a traditional Net Present Value (NPV) rule can lead to overinvestment. They also find that time-to-build magnifies the depressive effect of increased uncertainty on investment spending. Milne and Whalley (2000) correct an error in Majd and Pindyck's model from 1987. Compared to a standard real option model under uncertainty with instantaneous investment, they find that longer time-to-build reduces the effects of increased project value volatility. Time-to-build therefore reduces the effect that will lead to a higher investment threshold. Bar-Ilan and Strange (1996) also claim that conventional results on the effect of price uncertainty in investments are reversed or weakened when there are lags. They find that it is even possible that an increase in uncertainty hastens the decision to invest. Sødal (2004) corrects Bar-Ilan and Strange (1996) and concludes that investment lags can lead to preemptive investment as they argue, but only for high levels of uncertainty.

Several empirical studies have contributed to the field of real options by supporting the results of theoretical models and concepts, and by showing that real option investment decisions rules are applicable to different investments decisions. Quigg (1993) finds empirical support for real option pricing models that incorporates the option to develop land. Moel and Tufano (2002) does an empirical study of mine closings and openings. They find strong support for real option models and the use of shutdown flexibility. Their results demonstrate that the decision to open a mine is related to market wide factors, mine specific factors and firm specific managerial factors. Bulan et al. (2009) show empirically that an increase in both idiosyncratic and systematic risk lead developers to delay new real estate investments based on an empirical study of condominium developments. Kellogg (2010) finds that oil companies respond to an increase in expected volatility by reducing their drilling activity by a magnitude consistent with real options theory. Fleten, Haugom and Ullrich (2012) investigate the option to shutdown, startup, and abandon existing peak load power plants and find strong evidence for real option effects. They find that hysteresis effects for shutting down operating plants and starting up shutdown plants increase with increased uncertainty about the outcome of deregulation of power markets. Their results show no evidence that regulatory uncertainty affects abandonment decisions.

The contributions from empirical studies show that real option analysis and techniques are valuable for real life decisions. There has, to the best of our knowledge, never been conducted any empirical studies of sequential investment decisions with time-to-build. The aim of this paper is to provide an empirical study of sequential investments. We will investigate how different factors influence electricity generating companies' decisions to postpone or cancel an investment process as opposed to continue investing. The context for these firms has become riskier and more complex (Gollier et al., 2005). Price and demand level uncertainties were the main concerns for decision makers before restructuring of electricity markets. Deregulation has increased the sources of uncertainty, and electricity producers must now account for both market risk and regulatory risk when making investment- or abandonment decisions. We use data originally collected by Fleten, Haugom and Ullrich (2012) and utilize a similar analytical approach. Our paper will proceed along the following lines. The next section describes the dataset and variables used in the analysis. In Section 3 we investigate the factors that influence the decision to deviate from the original investment schedule and postpone or cancel a project. Section 4 compares different degrees of irreversibility and how it affects sequential investments. A conclusion and possible extensions to this empirical study is presented in Section 5.

# 2 Data and Variable Description

In this section we will describe the data and variables used in the analysis. The main sources of raw data are the Energy Information Administration (EIA), wholesale electricity market operators and the U.S. Environmental Protection Agency. The proposed peak load plants in our dataset are from the three wholesale electricity markets- Pennsylvania-New Jersey-Maryland(PJM), the New England Independent System Operator (ISO-NE), and the New York Independent System Operator (NYISO). The dataset covers the time period 2001-2009 and contains 2926 plant-year observations on 396 individual plants. Table 9 in the appendix presents summary statistics for macroeconomic-, uncertainty- and firm specific variables. We also refer to the appendix for time series plots of macroeconomic variables.

## 2.1 Generators

Our main analysis evaluates proposed simple cycle combustion turbines fueled by natural gas (NG) or diesel (DFO). These generators are typically used for peak load production and can easily be ramped up and down to meet the fluctuating demand in the market. We only use combustion turbines in our main analysis due to lack of heat rate data for other prime movers.[1]. Combustion turbines generally have a time-to-build of two years (EIA, 2003).

## 2.2 Status Changes

We use status codes from the annual EIA form 860 reports (shown in Table 1) to determine the yearly status of a proposed generator. The codes can be considered as stages of the sequential investment in a generator.

*Table 1: Status codes*

| Stage | Status Code | Description |
|---|---|---|
| 1 | P | Planned, no regulatory approval received |
| 2 | L | Planned, regulatory approvals pending |
| 3 | T | Planned, regulatory approvals received |
| 4 | U | Planned, under construction <50% |
| 5 | V | Planned, under construction >50% |
| 6 | TS | Planned, construction complete but not in operation |
| 7 | OP | Existing, operating |
| - | IP | Planned, canceled before completion |

[1]The heat rate is a measure of efficiency used to calculate the spark spread (Section 2.3)

A firm that is planning to build a generator has three mutually exclusive choices to make. They can continue investing, or deviate from their plan by either postponing or canceling the project. Their decision in year $t$ is revealed in the year $t+1$ EIA form 860 report. We define *proceeding* as progression from a planned status in year $t$, to a more complete stage in year $t+1$. In addition we define generators under construction as proceeding if they remain in status U or V for a maximum of two years because of time-to-build. *Postponing* is staying in the same planned status from one year to the next, except generators under construction as explained above.[2] *Canceling* is moving from any of the planned statuses in year $t$, to canceled in year $t+1$. Figure 1 documents the occurrences of decisions to proceed, postpone and cancel in the years 2002-2009.

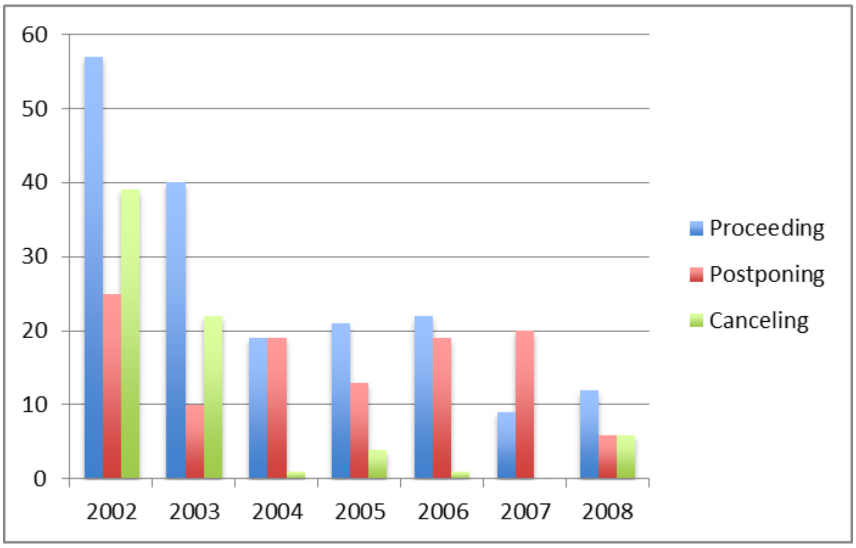



*Figure 1: Occurrences of yearly transitions*

## 2.3 Uncertainty Factors

The electricity supply industry in the US has traditionally been dominated by privately owned utilities, regulated by public regulatory commissions. The utilities had (or still have) a monopolistic position in the area they served and prices were determined by tariffs. The Energy Policy Act of 1992 started a nationwide effort to open for reliance on markets in the electricity supply system (Wangensteen, 2011). Deregulation is taking place at the state level and we use a retail competition index defined by Fleten, Haugom and Ullrich (2012) to determine if there is regulatory uncertainty in a state. The retail competition index is a set of discrete variables ranging from 1 to 5, which correspond to:

[2]In the postponing scenario, we do not know whether the project owner made a decision to postpone, or if there are other circumstances influencing the delay. Reasons for an unchanged status can be delays in regulatory approval or construction. We assume that regulatory approvals do not take more than a year and that the construction process of combustion turbines is well known with low probability of delays. Hence, the definition of postponing should be acceptably accurate.

1. No activity
2. Investigation underway
3. Competition recommended
4. Law passed requiring retail competition
5. Competition implemented.

This index is created with information from a descriptive summary of state-level deregulation published by EIA, and state utility commission information. Regulatory uncertainty is defined as a binary variable equal to one if there is uncertainty about deregulation in a given area, and zero otherwise. When the retail competition index has the value of 2, it is uncertain whether the state will implement competition. When the value is 3, there is uncertainty about the final form of the retail competition. The regulatory uncertainty variable is therefore one if the index is 2 or 3, and zero if it is 1, 4 or 5.

The event of deregulation can affect utilities either positively or negatively. Producers with low costs will benefit from retail competition, and they will capture a bigger part of the demand (Wangensteen, 2011). This may in turn create incentives to invest in new, low cost capacity. Generators with high costs that were profitable before deregulation may become unprofitable with retail competition as a result of lower prices. Companies also face the possibility of stranded costs when there is regulatory uncertainty. If investments in high capacity plants are made before deregulation and there is an overcapacity on the generating side leading to low prices, generating companies may suffer substantial losses. In this context these costs are defined as stranded (Wangensteen, 2011).

Spark spread is the difference between the price of electricity and the cost of generation (McDonald, 2006). The cost is the product of the fuel price and the generator specific heat rate[3]. The spark spread is given by:

$$SPRD_{ijk,n} = P^{elec}_{k,n} - HR_i \times P^{fuel}_{jk,n} \tag{1}$$

Where

| | |
|---|---|
| $SPRD_{ijk,n}$ | is the spark spread for generator $i$, burning fuel $j$, in region $k$, on day $n$ |
| $P^{elec}_{k,n}$ | is the electric price in region $k$ on day $n$ |
| $HR_i$ | is the generator $i$ heat rate (measure of efficiency) |
| $P^{fuel}_{jk,n}$ | is the price of fuel $j$ in region $k$, on day $n$ |

Fuel prices correlate positively with electricity prices, and higher electricity prices will not necessarily result in higher profits, neither will low fuel prices. The spark spread is

[3]We consider only electricity and fuel prices and have chosen to ignore distribution-, maintenance-, emission- and other costs.

therefore a better profitability measure than looking at electricity prices and fuel prices individually. Another benefit of using the spark spread is that a single reference value makes the analysis of sequential investment less complicated (Näsäkkäla and Fleten, 2005). The annual average spark spread standard deviation is our second measurement of uncertainty and it is calculated as follows:

$$SPRDSD_{ijk,t} = STDEV_{n=1}^{T}(SPRD_{ijk,n}) \tag{2}$$

Where

| | |
|---|---|
| $SPRDSD_{ijk,t}$ | is the standard deviation of the spark spread for generator $i$, burning fuel $j$, in region $k$, in year $t$ |
| $T$ | is the number of days in year $t$ |

The spark spread standard deviation for a proposed generator is only a theoretical construct. It is a representation of what the spark spread would have been if the generator was operating. Adding a new generator to the grid would in theory influence the supply of electricity and demand for fuel. The price of electricity and fuel would therefore be slightly different changing the true value of the spark spread standard deviation.

The peak load plant value is the discounted sum of expected cash flows minus operational costs plus the option value of being able to ramp up and down (Näsäkkäla and Fleten, 2005). Increased spark spread volatility has two different effects on investment behavior. The first effect is that higher spark spread volatility increases the value of the peak load plant because of the ability to ramp up and down. Firms should therefore be more hesitant to postpone or cancel a planned project. The second effect is the option to wait for more information in periods of price uncertainty. Majd and Pindyck (1987) show that time-to-build magnifies the depressive effect of increased uncertainty on investment spending. Since an increase in spark spread standard deviation increases the value of the power plant but also increases uncertainty it has an ambiguous effect. To be able to resolve the ambiguity we would have to distinguish between the short term and long term effects of uncertainty in the spark spread. The spark spread standard deviation variable defined above cannot separate these properties. Näsäkkäla and Fleten (2005) model the spark spread allowing mean reversion in short-term variations and uncertainty in the equilibrium price to which prices revert. They find that an increase in short term variations make a peak load plant more attractive, whereas an increase in long term uncertainty makes base load plants more favorable by postponing the upgrade threshold. The effect of increased spark spread volatility resulting in increased value of the peak load plant seems to be more prominent in our dataset. Uncertainty in equilibrium prices resulting from fundamental changes that are expected to persist could also affect investment decisions in the future. The impact of deregulation and new technologies are examples of such fundamental changes.

## 2.4 Macroeconomic Factors

Variations in the state of the economy influence the level of investments in most sectors. Interest rates influence financing costs of new capacity and the value of discounted cash flows. We examine the effects of varying interest rates by looking at the risk free, ten-year treasury notes. In addition, we examine the credit spread between utility bonds and the risk free rate. This is an indicator of the level of risk premium demanded by investors, and we use it as a proxy for credit risk in the utility industry. A higher credit spread reflects more risk in utility investments, and increases financing costs relative to the risk free rate[4]. Hence, it should have a negative effect on investments. Annual average interest rates are collected from the AEO report published by the EIA. Credit spreads are quoted as the net additional yield between utility bonds and US treasury notes according to:

$$Spread_t = AAU_t - T10_t \tag{3}$$

Where
$AAU_t$ is the year $t$ average utility bond interest rate (rated AA)
$T10_t$ is the year $t$ average 10-year US treasury note interest rate (rated AAA)
$Spread_t$ is the year $t$ credit spread between $AAU_t$ and $T10_t$

Electricity is consumed at the same time it is produced, and it is not possible to store significant quantities in an economic manner (Wangensteen, 2011). There has to be excess production capacity in order to avoid blackouts in periods of high demand. The excess capacity is called reserve margin, and it influences the electricity price negatively when it rises (Fleten, Haugom and Ullrich, 2012). A low reserve margin should encourage investment in new capacity. Utilities may evaluate forecasts of the reserve margin when they consider a new generator since it influences future profitability. We use a 3-year average reserve margin in order to capture the effect of both the current year, and the forecasted reserve margin for the next two years. Capacity and demand data is collected from NERC's Electricity Supply and Demand (ES&D) database, and the reserve margin variable is calculated as follows:

$$RM_{k,t}^{avg} = \frac{RM_{k,t} + RM_{k,t}^{1} + RM_{k,t}^{2}}{3} \tag{4}$$

Where
$RM_{k,t}$ $= \frac{(C_{k,t} - D_{k,t})}{D_{k,t}}$
$C_{k,t}$ is the year $t$ capacity in region $k$

[4]We consider the credit spread variable to be exogenous because the impact of decisions in our firm sample is unlikely to influence the nationally quoted utility bond interest rate that is used.

| | |
|---|---|
| $D_{k,t}$ | is the year $t$ peak demand in region $k$ |
| $RM_{k,t}$ | is the year $t$ reserve margin for region $k$ |
| $RM_{k,t}^1$ | is year $t$ forecasted reserve margin for year $t+1$ in region $k$ |
| $RM_{k,t}^2$ | is year $t$ forecasted reserve margin for year $t+2$ in region $k$ |
| $RM_{k,t}^{avg}$ | is the 3-year average reserve margin |

## 2.5 Firm Specific Factors

We have created a utility type variable describing the firm's main business area. We have set the binary variable to one if the main objective is electricity sales. This group includes generators owned by municipalities as well as Investor Owned Utilities (IOUs). We define these firms as *electric utilities*. The variable is zero when the core competencies are within other businesses such as pharmaceuticals, universities, airports and land development. Hereafter we refer to this group as *non-electric utilities*. The main objective for these generators is expected to be backup power generation. We use this variable to analyze the behavioral difference between the two utility types. 11,5% of the proposed generators in the main dataset are owned by non-electric utilities.

We have two measures of the total size of the firms. These measures are total installed capacity and total number of existing generators owned by the firms. The two variables are 0,93 correlated and we use the total number of existing generators as a measure of the company size in the regressions. This variable has the most explanatory power based on univariate statistics and individual regressions. As project specific financial data was difficult to obtain, we propose that this variable to some extent indicate a firm's financial capabilities. Larger companies may have managerial expertise and the benefit of economies of scale allowing them to economically expand capacity when smaller firms can not.

# 3 The Decision to Postpone or Cancel Sequential Investments

Variations in the factors introduced in the last section may influence the value of deviating from the original investment schedule. In this section we investigate how these factors affect decisions to postpone or cancel a proposed combustion turbine.

## 3.1 Decisions to Postpone

There are a total of 112 occurrences where firms are postponing, and 204 where they proceed with investment. Table 2 documents the univariate statistics for the factors in these two samples. The delta column shows the difference in mean and the level of significance. Individual and multivariate regression statistics are provided in Table 3. Figure 2 shows predictions of the probabilities of postponing as functions of spark spread volatility, reserve margin, firm size and credit spread.

### 3.1.1 Univariate Statistics

The regulatory uncertainty variable has the most significant difference in mean between the observations of postponing and proceeding. It tells us that only 7,1% of the observations of postponing took place under uncertainty compared to 34,3% of the observations where they decided to proceed. The difference in spark spread volatility mean is also significant, with a lower mean when firms are postponing. We observe that companies that are waiting own fewer generators on average and that there is no significant difference in the risk free interest rate between the samples. The reserve margins and credit spreads are, contrary to intuition, significantly lower in the cases where firms decided to postpone.

*Table 2: The table presents univariate statistics for uncertainty variables, macroeconomic variables, firm-specific variables and plant specific variables for plants which proceeded and plants that postponed. ***, ** and * describes 1%, 5% and 10% significance level respectively.*

| Type | Variable | Postponing | Proceeding | Delta | |
|---|---|---|---|---|---|
| Uncertainty | REGUNCERT | 0,071 | 0,343 | -0,272 | *** |
| | SPRDSD [$/MWh] | 0,025 | 0,027 | -0,002 | * |
| Macro | T10[%] | 4,447 | 4,441 | 0,006 | |
| | SPREAD [%] | 1,768 | 2,091 | -0,323 | *** |
| | RM [%] | 18,801 | 19,567 | -0,767 | * |
| Firm | TYPE | 0,983 | 0,951 | 0,031 | * |
| | TG | 17,152 | 24,240 | -7,088 | *** |
| Plant | SIZE [MW] | 0,096 | 0,101 | -0,005 | |
| | Observations | 112 | 204 | | |

### 3.1.2 Individual and Multivariate Regressions

We use the multivariate binary logit regression in equation (5) to analyze decisions to postpone. The correlations between the variables are provided in Table 10 in the Appendix.

$$\begin{aligned} DV_{i,t}^{postponing} = {} & \beta_0 + (\beta_1 \times REGUNCERT_{k,t}) + (\beta_2 \times SPRDSD_{ijk,t}) + (\beta_3 \times T10_t) \\ & + (\beta_4 \times SPREAD_t) + (\beta_5 \times RM_{k,t}^{avg}) + (\beta_6 \times TYPE_i) + (\beta_7 \times TG_{i,t}) \\ & + (\beta_8 \times SIZE_i) + \epsilon \end{aligned} \tag{5}$$

Where

| | |
|---|---|
| $DV_{i,t}^{postponing}$ | is the binary dependent variable which is one if a firm postponed generator $i$ in year $t$, and zero if they proceeded with investment |
| $REGUNCERT_{k,t}$ | is an indicator variable which is one if there is regulatory uncertainty in region $k$ for year $t$, and zero otherwise |
| $SPRDSD_{ijk,t}$ | is the spark spread standard deviation for generator $i$, burning fuel $j$, in region $k$, in year $t$ |
| $T10_t$ | is the ten year US Treasury note interest rate in year $t$ |
| $SPREAD_t$ | is the utility bond credit spread in year $t$ |
| $RM_{k,t}^{avg}$ | is the three-year average reserve margin in region $k$, in year $t$ |
| $TYPE_i$ | is an indicator variable which is one if generator $i$ is owned by an electric utility, and zero otherwise |
| $TG_{i,t}$ | is the total number of existing generators owned by the owner of generator $i$, in year $t$ |
| $SIZE_i$ | is the generator $i$ capacity |

The two most important independent variables appear to be regulatory uncertainty and credit spread looking at the individual regressions in Table 3. This ranking is based on the goodness of fit measures Pseudo-$R^2$, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and log likelihood. The preferred individual regression models are the ones who have the lower AIC and BIC measures and highest pseudo-$R^2$ and log likelihood measures.

Regulatory uncertainty is significant at 1% for the univariate statistics, individual regression and full regression. The average marginal effect is negative suggesting that regulatory uncertainty decreases the probability of postponing with 33,4%. Uncertainty about deregulation implies that owners are unsure about the future profitability of their plants. We expected, in accordance with Majd and Pindyck (1987), that firms are more likely to postpone proposed generators when there is uncertainty about retail deregulation. Fleten, Haugom and Ullrich (2012) found evidence that plant owners delay the decision to startup a plant which was previously shutdown, until the outcome of

*Table 3: The table presents the average marginal effects (dProb(Postponing)/dx) for each independent variable both individually and in the multivariate analysis. The last column represents the results of the full regression. The average marginal effects for $REGUNCERT_{k,t}$ and $TYPE_i$ are measured for the discrete change from zero to one.*

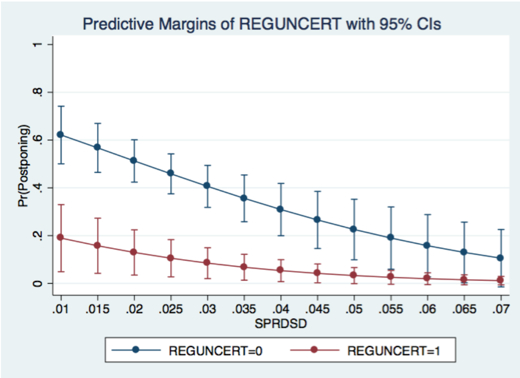
| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| REGUNCERT | -0,334 | *** | | | | | | | -0,359 | *** |
| SPRDSD | | -3,368 | * | | | | | | -8,957 | *** |
| T10 | | | 0,940 | | | | | | -9,447 | |
| SPREAD | | | | -17,630 | *** | | | | -27,061 | *** |
| RM | | | | | -1,573 | ** | | | -2,148 | *** |
| TYPE | | | | | | 0,138 | | | 0,071 | |
| TG | | | | | | | -0,002 | ** | -0,004 | *** |
| SIZE | | | | | | | | -0,365 | 0,369 | |
| Pseudo-$R^2$ | 8,07% | 0,50% | 0,00% | 4,62% | 0,94% | 0,53% | 1,31% | 0,15% | 23.78% | |
| Log pseudolikelihood | -188,87 | -204,42 | -205,44 | -195,95 | -203,51 | -204,37 | -202,75 | -205,14 | -156,58 | |
| AIC | 381,73 | 412,84 | 414,88 | 395,90 | 411,01 | 412,73 | 409,50 | 414,29 | 331,16 | |
| BIC | 389,24 | 420,35 | 422,39 | 403,41 | 418,53 | 420,24 | 417,01 | 421,80 | 364,97 | |

the deregulation process was more certain. Billingsley and Ullrich (2012) also found that regulatory uncertainty in electricity markets reduces capital investments. We get the opposite result. Figure 2 illustrates a big difference in the predicted probability of postponing between areas with and without regulatory uncertainty. Results obtained in Section 4 show that firms are more likely to proceed with investments in smaller combustion turbines in times of regulatory uncertainty compared with larger more complex prime movers. We argue that the reason is decreased irreversibility, modularity and reduction of potential stranded costs.

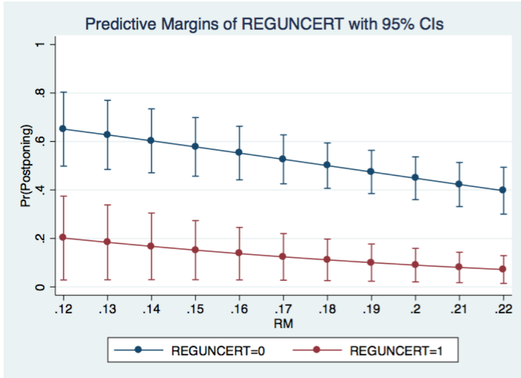
Spark spread standard deviation is significant at the 10 % level in the univariate statistics and individual regression. In the multivariate regression it is more significant with a negative average marginal effect. This result predicts that the probability of postponing decreases with higher volatility in the spark spread. The value of an operating peak load plants increases with higher spark spread standard deviation and therefore encourages project completion.

The difference in reserve margin is significant at the 10% level in the univariate statistics and individual regression. Together with the other explanatory variables it is significant at 1 %. The average marginal effect is negative suggesting that a higher reserve margins decrease the probability of postponing. This is the opposite of what we expected. To further explain this observation it is interesting to look at the direction of causality between the investments and the reserve margin. We performed a Granger causality test to be able to investigate the direction of causality. In this test the dependent variable is regressed on its own lagged values and the lagged values of the reserve margin. This was not possible with our dataset however, because of collinearity issues. To rule out feedback effects in the regression we compared the total installed new capacity of combustion turbines with the total existing capacity in a specific year and region. We find that this ratio is always less than 1%. Hence, the capacity contribution of new combustion turbines does not significantly influence the reserve margin. Based on this analysis we find it difficult to give a reasonable explanation for the sign of the average marginal effect of the reserve margin.

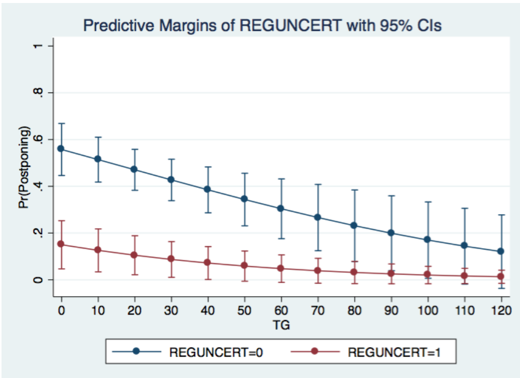
The predictive margins from Figure 2(d) show that the combination of low credit risk and no regulatory uncertainty results in a high probability of waiting. This is the opposite of what we expected. We refer to section 4 for a suggested explanation of the counterintuitive results.



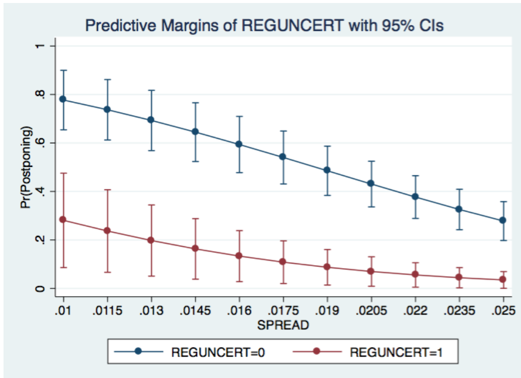

(a) Predicted probability of postponing as a function of spark spread standard deviation




(b) Predicted probability of postponing as a function of reserve margin




(c) Predicted probability of postponing as a function of firm size




(d) Predicted probability of postponing as a function of utility spread

*Figure 2: Predicted probability of postponing as functions of the significant variables separated by the regulatory uncertainty index (1 = uncertainty).*

## 3.2 Decisions to Cancel

The purpose of this section is to investigate the factors that may affect a firm's decision to cancel a planned investment project. There were 73 cancelations of planned generators in our data, none of which had started construction. Table 4 presents univariate statistics. The results from the individual- and multivariate logit regressions are given in Table 5. Figure 3 predicts the probability of canceling as functions of sparks spread volatility, firm size, generator size, interest rate.

### 3.2.1 Univariate Statistics

The difference in the reserve margin means is significant at the 1% level. The reserve margin which serves as a proxy for future profitability, is on average higher when proposed generators are canceled. This is what we expected because a high reserve margin indicates lower future profitability. The interest rate is lower on average and the credit spread is higher on average when generators are canceled. We also observe that smaller firms and non-electric utilities tend to cancel more often. These differences in mean are significant at the 1% level. The spark spread standard deviation is on average lower when generators are canceled and the cancelations take place when there is less regulatory uncertainty.

*Table 4: The table presents univariate statistics for uncertainty variables, macroeconomic variables, firm-specific variables and plant specific variables for plants which proceeded and plants that were canceled. ***, ** and * describes 1%, 5% and 10% significance level respectively.*

| Type | Variable | Canceling | Proceeding | Delta | |
|---|---|---|---|---|---|
| Uncertainty | REGUNCERT | 0,219 | 0,343 | -0,124 | ** |
| | SPRDSD [$/MWh] | 0,021 | 0,027 | -0,006 | *** |
| Macro | T10[%] | 4,332 | 4,441 | -0,109 | ** |
| | SPREAD [%] | 2,406 | 2,091 | 0,315 | *** |
| | RM [%] | 20,581 | 19,567 | 1,013 | *** |
| Firm | TYPE | 0,795 | 0,951 | -0,156 | *** |
| | TG | 12,000 | 24,240 | -12,240 | *** |
| Plant | SIZE [MW] | 0,126 | 0,101 | 0,025 | *** |
| | Observations | 73 | 204 | | |

### 3.2.2 Individual and Multivariate Regressions

We use the following binary logit regression in our analysis of decisions to cancel:

$$\begin{aligned} DV_{i,t}^{canceling} = \beta_0 &+ (\beta_1 \times REGUNCERT_{k,t}) + (\beta_2 \times SPRDSD_{ijk,t}) + (\beta_3 \times T10_t) \\ &+ (\beta_4 \times SPREAD_t) + (\beta_5 \times RM_{k,t}^{avg}) + (\beta_6 \times TYPE_i) + (\beta_7 \times TG_{i,t}) \\ &+ (\beta_8 \times SIZE_i) + \epsilon \end{aligned} \tag{6}$$

Where

$DV_{i,t}^{canceling}$ is the binary dependent variable which is one if the firm canceled a proposed generator $i$ in year $t$, and zero if they proceeded. All other variables are defined as in Section 3.1.

Based on the individual regressions the factors that seem to be the most important are the standard deviation of spark spread, the credit spread and the firm size respectively. This ranking is based on goodness of fit measures.

*Table 5: The table presents the average marginal effects (dProb(Canceling)/dx) for each independent variable both individually and in the multivariate analysis. The last column represents the results of the full model. The average marginal effects for $REGUNCERT_{k,t}$ and $TYPE_i$ are measured for the discrete change from zero to one.*

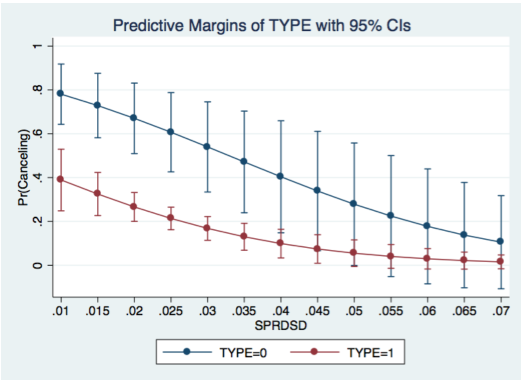
| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| REGUNCERT | -0,112 * | | | | | | | | 0,047 |
| SPRDSD | | -14,994 *** | | | | | | | -9,880 *** |
| T10 | | | -15,397 ** | | | | | | -15,810 ** |
| SPREAD | | | | 23,993 *** | | | | | 10,061 |
| RM | | | | | 2,833 *** | | | | -0,812 |
| TYPE | | | | | | -0,370 *** | | | -0,367 *** |
| TG | | | | | | | -0,005 *** | | -0,004 *** |
| SIZE | | | | | | | | 1,259 *** | 1,896 *** |
| Pseudo-$R^2$ | 1,26% | 6,29% | 1,49% | 6,10% | 2,40% | 4,37% | 4,50% | 2,77% | 22,96% |
| Log pseudolikelihood | -157,74 | -149,70 | -157,37 | -150,01 | -155,93 | -152,77 | -152,57 | -155,32 | -123,07 |
| AIC | 319,48 | 303,41 | 318,74 | 304,02 | 315,85 | 309,54 | 309,13 | 314,64 | 264,15 |
| BIC | 326,72 | 310,65 | 325,98 | 311,27 | 323,10 | 316,79 | 316,38 | 321,89 | 296,76 |

The regulatory uncertainty variable is not significant in the multivariate regression. It seems that, when all variables are considered, regulatory uncertainty does not affect the decision to cancel a planned generator. Fleten, Haugom and Ullrich (2012) find no evidence that regulatory uncertainty affects abandonment decisions for installed plants. For larger and more complex power plants however, regulatory uncertainty is significantly higher on average when planned investment projects are canceled (see Section 4).

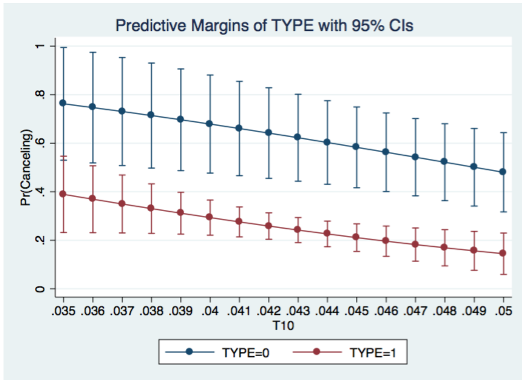
The standard deviation of the spark spread is significant at the 1% level in both the individual and full regression. The average marginal effect indicates that when the spark spread volatility is lower, the probability of canceling increases. Since the value of a peak load combustion turbine decreases with decreasing volatility it is reasonable that more firms cancel a proposed generator when the standard deviation of the spark spread decreases. Fleten, Haugom and Ullrich (2012) find similar results for the abandonment of existing generators.

The interest rate variable is significant in both regressions. The average marginal effect shows that the probability of canceling decreases when the interest rates increases. In a standard model an increase in interest rate reduces investment by raising the cost of capital and reduces the present value of future cash flows. Hence we would expect that an increase in interest rates would lead to higher probability of canceling. We provide an explanation to this finding in Section 4. The average marginal effect of the reserve margin is not in the multivariate regression. Billingsley and Ullrich (2012) find that, during periods of regulatory uncertainty, the electricity industry pays less attention to reserve margins.

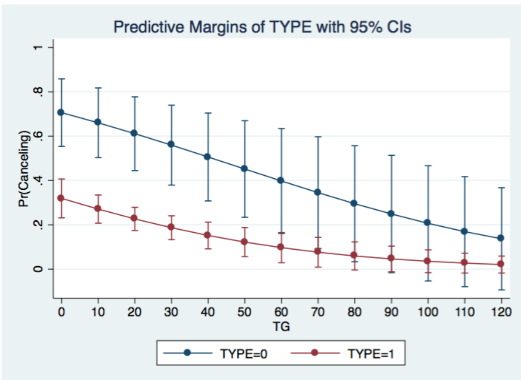
The utility type variable is significant both in the individual- and full regression. Our results indicate that non-electric utilities are more likely to cancel a planned project. The regression results also indicate that utilities owning a smaller total number of plants tend to cancel their planned investment projects more than utilities owning a larger total number of plants. We propose that this might be the result of the ability of larger utilities to finish a less profitable project that is part of their long-term strategy.



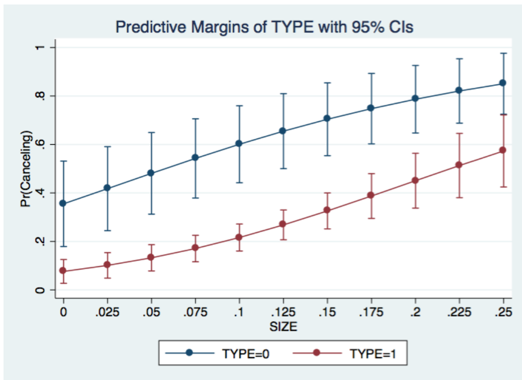

(a) Predicted probability of canceling as a function of spark spread standard deviation




(b) Predicted probability of canceling as a function of interest rate




(c) Predicted probability of canceling as a function of firm size




(d) Predicted probability of canceling as a function of generator size

*Figure 3: Predicted probability of postponing as functions of the significant variables separated by utility type (1 = electric utility).*

## 3.3 Multinomial Logit Regression

A multinomial logit regression reveal how each variable affects the probability of postponing or canceling in comparison to the observations where firms are proceeding (base). This regression allows us to consider all decisions simultaneously and is modeled as follows:

$$\begin{aligned} DV_{i,t}^{multi} = \beta_0 &+ (\beta_1 \times REGUNCERT_{k,t}) + (\beta_2 \times SPRDSD_{ijk,t}) + (\beta_3 \times T10_t) \\ &+(\beta_4 \times SPREAD_t) + (\beta_5 \times RM_{k,t}^{avg}) + (\beta_7 \times TYPE_i) \\ &+(\beta_8 \times TG_{i,t}) + (\beta_9 \times SIZE_i) + \epsilon \end{aligned} \tag{7}$$

Where

$DV_{i,t}^{multi}$ is an indicator variable equal to zero if the company invested(base), one if the company waited and two if the company canceled a generator $i$ in year $t$. All other variables are defined in section 3.1

The results of the regression analysis are presented in Table 6. The table shows the average marginal effects of each independent variable and tells us how the variable affects the probability of postponing and canceling as opposed to the base category (proceeding). Most of the variables have the same effect on the probability of postponing and canceling as we found in section 3.1 and 3.2. This indicates that the results from section 3.1 and 3.2 still hold when considering all decisions simultaneously. There are two exceptions. The credit spread now shows a significant effect on the probability of canceling. The second effect is that the utility type variable is significant at the 5% level in the multinomial regression and has a positive effect on the probability of postponing. It seems reasonable that electric utilities utilize the option to wait more than non-electric utilities because of their different objectives.

*Table 6: The table presents the average marginal effect of each independent variable on the probability of postponing and canceling as opposed to the probability of proceeding. The last column presents the results from the full regression. ***, ** and * describes 1%, 5% and 10% significance level respectively.*

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Postponing | REGUNCERT | -0,267 *** | | | | | | | | -0,299 | *** |
| | SPRDSD [$/MWh] | | 1,273 | | | | | | | -6,503 | ** |
| | T10 [%] | | | 5,492 *** | | | | | | 2,177 | |
| | SPREAD [%] | | | | -20,555*** | | | | | -25,434 | *** |
| | RM [%] | | | | | -2,135 *** | | | | -1,539 | * |
| | TYPE | | | | | | 0,230 *** | | | 0,153 | ** |
| | TG | | | | | | | -0,001 *** | | -0,002 | ** |
| | SIZE [MW] | | | | | | | | -0,704 | -3,05 | |
| Canceling | REGUNCERT | -0,023 | | | | | | | | -0,092 | |
| | SPRDSD [$/MWh] | | -11,247*** | | | | | | | -5,674 | * |
| | T10 [%] | | | -13,289 | | | | | | -14,721 | *** |
| | SPREAD [%] | | | | -22,258*** | | | | | 13,338 | *** |
| | RM [%] | | | | | 2,410 *** | | | | -3,433 | |
| | TYPE | | | | | | -0,395 *** | | | -0,353 | *** |
| | TG | | | | | | | -0,003 *** | | -0,002 | ** |
| | SIZE [MW] | | | | | | | | 1,147 *** | 1,466 | *** |
| | Pseudo-$R^2$ | 4,25% | 2,80% | 0,75% | 6,90% | 1,98% | 2,81% | 2,09% | 1,63% | 22,69% | |
| | Log pseudolikelihood | -157,74 | -149,70 | -157,37 | -150,01 | -155,93 | -152,77 | -152,57 | -155,32 | -304,02 | |
| | AIC | 761,11 | 772,50 | 788,60 | 740,21 | 778,98 | 772,41 | 778,06 | 781,67 | 644,04 | |
| | BIC | 776,96 | 788,35 | 804,46 | 756,07 | 794,84 | 788,27 | 793,91 | 797,52 | 715,38 | |

# 4 The Effect of Irreversibility on Investment Decisions

Irreversibility of investments is an important assumption in real options theory. Dixit and Pindyck (1994) define investment expenditures as sunk cost when they are firm or industry specific. Pindyck (1988) examines implications of irreversibility for capacity choice. With a simplified model he shows that for marginal investment decisions, and during times of uncertainty, a firm's optimal capacity choice is much smaller than it would be if investments were reversible. The relatively low capital cost for one simple cycle combustion turbines (GT), combined with possibilities for resale in the second hand market, makes these turbines only partly irreversible[5]. It is cheaper per unit of capacity to build a large power plant than adding capacity in small amounts. This modularity however, gives the utility flexibility when facing uncertainty in demand (Dixit and Pindyck, 1994). In this section we investigate how irreversibility affects sequential investments in different prime movers.

In this analysis we use a dataset consisting of steam turbines (ST), combined cycle single shaft (CS) and combined cycle steam parts (CA) with capacities above 150 MW as a comparison basis. This data covers the same time period and areas as the main dataset. Table 7 shows summary statistics for both datasets. The mean capacity of the combustion turbines (GT) is 116 MW while the other prime movers (CA,CS,ST) has a mean capacity of 269 MW. Hence, the alternative dataset consists of larger, more complex generators with longer time-to-build (EIA, 2003).

*Table 7: Summary statistics for the main and alternative dataset*

| | Main Dataset | Alternative Dataset |
|---|---|---|
| Prime mover | GT | CA,CS,ST |
| Number of generators | 173 | 30 |
| Mean [MW] | 116 | 269 |
| SD [MW] | 6 | 8 |
| Min [MW] | 4,2 | 167 |
| Max [MW] | 250 | 420 |
| Time-to-build [years] | 2 | >3 |

Univariate statistics are given in Table 8. The main finding from this analysis is that, on average, the larger generators are more likely to proceed in the sequential investment process without regulatory uncertainty. This is consistent with real option theory, stating that less uncertainty decrease the value of waiting for more information and increases the incentive to invest (Majd and Pindyck, 1987). The main dataset however does not give this result. We suspect that the reason is less irreversibility, modularity and shorter time-to-build for GTs. Under times of uncertainty utilities invest in GTs rather than larger and more irreversible ST, CS and CAs. Tesiberg (1994) shows that there is value in shorter time-to-build and flexibility to delay and abandon construction of

[5]We consider combustion turbines not to be fully industry specific.

power plants under regulatory uncertainty. Billingsley and Ullrich (2012) point out that regulatory uncertainty implies uncertainty concerning the ability of a utility to recover capital cost. Utilities therefore fill inn long-term planned investments with lower initial cost technologies to mitigate concerns about the ability to recover capital costs.

We also find that larger, more complex turbines proceed to the next investment stage more on average when the interest rate is lower. This can explain the negative effects of low interest rate on investment in the main dataset. Because the cost of capital increases with higher interest rates, the utilities rather invest in smaller, less capital-intensive combustion turbines with modularity options when interest rates are high.

*Table 8: The table presents univariate statistics for uncertainty variables, macroeconomic variables and plant specific variables for plants which proceeded and plants that were canceled for the main dataset and the alternative dataset. ***, ** and * describes 1%, 5% and 10% significance level respectively.*

| | | Alternative Dataset | | | Main Dataset | | |
|---|---|---|---|---|---|---|---|
| Type | Variable | Canceling | Investing | | Canceling | Investing | |
| Uncertainty | REGUNCERT | 0,219 | 0,343 | ** | 0,265 | 0,070 | *** |
| Macro | T10 [%] | 4,33 | 4,44 | ** | 4,73 | 4,36 | *** |
| | SPREAD[%] | 2,41 | 2,09 | *** | 2,27 | 2,11 | |
| | RM [%] | 20,58 | 19,57 | *** | 18,08 | 18,89 | |
| Firm | TG | 12,00 | 24,24 | *** | 6,69 | 27,01 | *** |
| Plant | SIZE [MW] | 126,14 | 101,44 | *** | 322,05 | 365,38 | |
| Observations | | 73 | 204 | | 49 | 71 | |

Even if the combustion turbines are less irreversible and have a lower cost of capital, real option theory should still apply to investment decisions. One would expect uncertainty and interest rate to affect investments in combustion turbines in the same direction as investments in larger plants even though the magnitude of the effect might be weakened. We find however that utilities are more likely to proceed with investments in combustion turbines during times of regulatory uncertainty and high interest rates. The short time-to-build, modularity and less irreversible characteristics seem to increase the value of these turbines under uncertainty. Utilities to some extent invest in new capacity despite regulatory uncertainty and high interest rates. In this context however they prefer proceeding with investments in smaller combustion turbines rather than larger plants due to the characteristics of combustion turbines mentioned above.

# 5 Conclusion

Most real life investment decisions are made sequentially over time. This paper provides an empirical study of the factors that affect decisions to postpone or cancel sequential investments with time-to-build. The analysis is based on proposed power plants in three major US wholesale electricity markets during the years 2001-2009.

We find that increasing spark spread volatilities decrease the probability of postponing or canceling a proposed peak load plant. This conforms to the fact that the value of an operating peak load plant increases with higher spark spread volatility. Uncertainty about deregulation increases the probability that firms proceed with sequential investments in simple cycle combustion turbines. We show that for larger and more complex power plants, regulatory uncertainty makes it less likely that firms continue investment projects. Our results indicate that, under times of uncertainty, utilities rather proceed with investments in less irreversible, less capital intensive projects with modularity and shorter time-to-build. This strategy reduces the potential stranded costs and increases flexibility. The reserve margin influences investment decisions in the opposite direction of what we would expect. In our analysis a lower reserve margin increases the probability of postponing but is not significant for cancelations. We find it difficult to provide a reasonable explanation for this result. Investigation of the effects of reserve margin on investments with time-to-build is an interesting topic for further research.

We recognize that our data has several limitations. The time resolution of one year makes it difficult to capture all the effects of time-to-build for investments with construction lags of only two years. Analyzing data covering a longer time period will also be beneficial for further research. A more thorough analysis of larger plants with longer time-to-build might reveal other effects than the ones found in this paper. It will also enable empirical investigation of whether the stylized results from Bar-Ilan and Strange (1996) and Sødal (2004) are applicable to real life investments.

# 6 Acknowledgements

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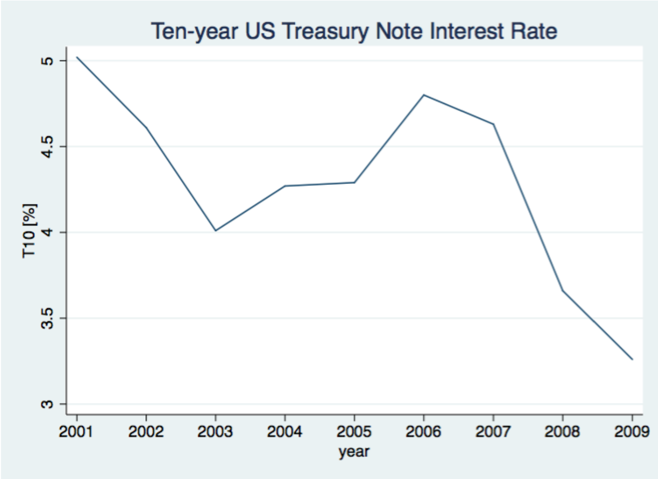
# A Appendix

*Table 9: Summary statistics for macroeconomic-, uncertainty- and firm specific variables*

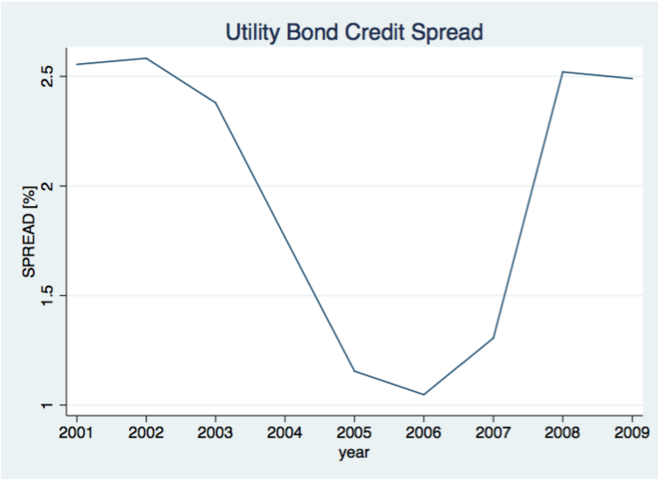
| Variable | Observations | Mean | Stdev | Min | Max |
|---|---|---|---|---|---|
| REGUNCERT | 389 | 0,24 | 0,43 | 0,00 | 1,00 |
| SPRDSD | 389 | 0,03 | 0,03 | 0,03 | 0,07 |
| T10 | 9 | 0,04 | 0,01 | 0,03 | 0,05 |
| SPREAD | 9 | 0,02 | 0,01 | 0,01 | 0,03 |
| RM | 18 | 0,19 | 0,04 | 0,12 | 0,22 |
| FP(DFO) | 33 | 10,72 | 4,31 | 5,38 | 16,68 |
| FP(NG) | 45 | 5,68 | 1,71 | 2,72 | 8,47 |
| TYPE | 389 | 0,93 | 0,25 | 0,00 | 1,00 |
| TG | 389 | 19,9 | 25,59 | 1,00 | 121,00 |
| SIZE | 389 | 0,1 | 0,06 | 0,00 | 0,25 |

*Table 10: Correlations between different variables*

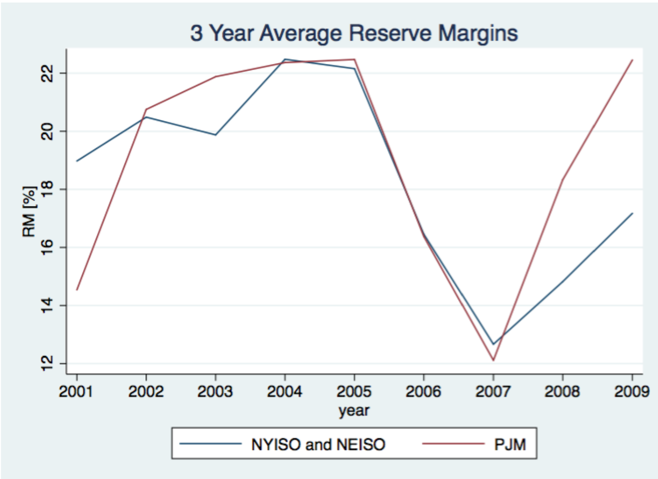
| | REGUNCERT | SPRDSD | T10 | SPREAD | RM | TYPE | TG | SIZE |
|---|---|---|---|---|---|---|---|---|
| REGUNCERT | 1,000 | | | | | | | |
| SPRDSD | -0,018 | 1,000 | | | | | | |
| T10 | -0,043 | 0,3856 | 1,000 | | | | | |
| SPREAD | 0,000 | -0,403 | -0,618 | 1,00 | | | | |
| RM | 0,013 | -0,605 | -0,445 | 0,383 | 1,000 | | | |
| TYPE | 0,081 | -0,027 | -0,010 | 0,039 | 0,006 | 1,000 | | |
| TG | 0,147 | 0,034 | -0,033 | -0,43 | -0,060 | 0,099 | 1,000 | |
| SIZE | 0,096 | -0,023 | 0,025 | 0,019 | 0,010 | 0,099 | 0,064 | 1,000 |




(a) 10-year US Treasury notes




(b) Utility bond credit spread




(c) Reserve margin in NYISE, NEISO and PJM

*Figure 4: Time series representations of macroeconomic variables*