NTNU – Trondheim
Norwegian University of
Science and Technology

# Sequential investment in gas fired power plants

A real options analysis

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## Preface

This master thesis is written as partial fulfillment of a Master of Science at the Norwegian University of Science and Technology (NTNU). The degree specialization is Financial Engineering (TIØ4550) at the Department of Industrial Economics and Technology Management.

We would like to thank our supervisor Stein-Erik Fleten at NTNU for professional guidance throughout the project. We also wish to thank Assistant Professor Carl Ullrich at James Madison University and Postdoctoral Fellow Erik Haugom at NTNU for their valuable input.

*Trondheim, 09.06.2014*

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**Abstract**

This paper presents an empirical analysis of the real options to postpone and cancel sequential investments with time-to-build. Utilizing generator level data that to the best of our knowledge is unique in scope and detail, we look at investments in gas fired combustion and combined cycle generators. We find strong evidence of real option effects. Regulatory uncertainty and profit uncertainty increases the probability of companies postponing and canceling investments. Firms postponing during times of uncertainty is as expected from theory; firms canceling under these conditions is somewhat more surprising.

**Sammendrag**

I denne masteroppgaven presenterer vi en empirisk analyse av realopsjoner på å utsette og avbryte sekvensielle investeringer i gasskraftverk hvor vi tar hensyn til tiden det tar å bygge kraftverkene. Datasettet som benyttes er unikt i omfang og detalj. Både investeringer i gassturbinverk og kombikraftverk er analysert, og vi finner støtte for at realopsjonseffekter er til stede i beslutningsprosessen. Regulatorisk usikkerhet og usikkerhet angående fortjenesten til gasskraftverkene øker sannsynligheten for at selskapene utsetter og avbryter investeringene. Det at beslutningstakere utsetter investeringer når de opplever usikkerhet er i tråd med realopsjonsteori, at de også avbryter investeringene under slike forhold er mer overraskende.

# Contents

# 1 Introduction

The purpose of this paper is to test for real option effects in sequential investment with time-to-build and explore other factors that influence investment behavior. Specifically we investigate the decisions to postpone, proceed and cancel investment in gas fired combustion and combined cycle generators. Our sample data includes observations for U.S. plants from 1991 to 2011. The dataset contains 37,821 generator-year observations for 3,748 individual generators and is as far as we know unique in scope and detail. A notable feature is that the dataset allows us to explicitly observe the decision to cancel an investment. Since the data contains information on the complete sample, including both planned projects and existing plants, we avoid exclusion bias.[1]

In the observation period, especially in the late 1990s and early 2000s, there was a lot of regulatory uncertainty as states evaluated restructuring measures. To test for real option effects we create a regulatory uncertainty variable. We also create a spark spread standard deviation variable to investigate real option effects as a consequence of profitability uncertainty.

We find strong real option effects for both uncertainty variables, with increased uncertainty leading companies to postpone investments. For canceling the findings are more surprising as higher uncertainty also lead to more cancellation.[2] The data is analysed using two separate regression analyses. The *full sample* regression includes all the years we have available data, i.e. 1991 to 2011. The second regression is the *spark spread sample* regression and contains data from the years 2003 to 2011. This regression includes the spark spread standard deviation variable that we could not create for the full regression due to a lack of wholesale price data for the beginning of the time interval.

Two important themes in the paper are regulatory uncertainty and the decision to cancel investments. We also focus on how the first affects the second. The decision to cancel is highly relevant for policy makers as it affects the reliability of supply and industry players will use their influence to keep changes that can yield this result from happening.

We contribute to real option literature by providing an empirical analysis of sequential investments, an area where there has been done little research. We also thoroughly investigate regulatory uncertainty and canceling, and provide arguments for why regulatory uncertainty may actually increase the probability of canceling under given circumstances, contrary to classic real option theory. The

[1] Exclusion bias occurs due to the systematic exclusion of certain individuals from the study.
[2] We discuss some possible explanations for this in Section 4.2.1 and 5.2.1.

implications this has for policy makers are also briefly discussed.

Following Brennan and Schwartz (1985) and McDonald and Siegel (1986), the pioneers of real option theory, Majd and Pindyck (1987) published a noteworthy contribution that is highly relevant to our study. They demonstrate that uncertainty should have a depressive effect on investment spending in a sequential investment process with time-to-build. These results match our findings. Even though most industry decision makers probably do not explicitly utilize real option valuation (Triantis, 2005), there may still exist some "rules of thumb" that factor in these effects (McDonald, 2000). Several empirical papers find evidence of real option effects, Quigg (1993) and Moel and Tufano (2002) are some examples. There have also been papers that look into regulatory uncertainty in the electricity generation industry. Ishii and Yan (2011) and Fleten et al. (2012), both find evidence of regulatory uncertainty having a depressing effect on investments. A more thorough review of the significant literature is presented in the following section.

There are several noteworthy trends in our observation period that may influence the results or the interpretation of the variables. One important phenomenon is the collapse of the merchant market[3]. Following an investment bubble in the late 1990s, there was a collapse in investments as many independent power producers went bankrupt. This is described by among others Finon (2008) and Joskow (2005). The consequence for our data is that a large number of observations are clustered in these years. Another trend is the missing money problem, i.e. a reduction in the equilibrium installed capacity in some deregulated markets. This comes as a consequence of the risk of capacity investment being moved from customers to generator owners in the deregulation process, while there exist market inefficiencies that keeps the companies from charging the scarcity value of electricity in situation of periodic shortage. Cramton and Stoft (2006) describes this phenomenon. Relevant literature on trends in the U.S. power market are presented in greater detail in Section 2.3.

The remainder of this paper is structured as follows, in Section 2 we present relevant literature. In Section 3 the dataset and the chosen variables are described. Section 4 discusses the results from the full sample regression and Section 5 the results from the spark spread sample regression. Section 6 gives a short summary of our main results. We then present our conclusions in Section 7. Appendix A contains graphical representations of variables and transitions between investment stages. Appendix B contains an extended statistical discussion of the results in the full sample regression. The source code used to build the dataset and run the regressions are written in **Stata** and is available from the authors.

[3]The merchant market refers to stand alone producers that sell all their production in the short term market, without long-term contracts (Finon, 2008).

# 2 Literature Review

In this chapter we first review the literature that lays the theoretical foundation for our investigation in section 2.1. We then look at empirical results from other studies in section 2.2, before we look at literature describing some developments in the U.S. power market that may be relevant to our study, in section 2.3

## 2.1 Theoretical

The theoretical foundation for our real option investigation should be seen in the context of earlier research on optimal investment decisions. Roberts and Weitzman (1981) created a model that focuses on the importance of information gathering and learning-by-doing in the investment process. The model reduces uncertainty regarding the completed project for each consecutive stage of the investment process. This way it can be profitable to continue with a project even though the NPV in the early stages is negative. Their research is mainly related to R&D projects. Bernanke (1983) and Cukierman (1980) consider irreversible investments with no time-to-build and find that the uncertainty regarding future returns creates an incentive to wait for more information before investing. This result is the opposite of that of Roberts and Weitzman (1981).

Financial options theory was developed in the 1970s in order to accurately evaluate the value and optimal exercise boundaries of financial options (Black and Scholes, 1973; Merton, 1973). Economists like Brennan and Schwartz (1985) and McDonald and Siegel (1986) pioneered real option theory as they realized option theory could be applied when evaluating real life investments. McDonald and Siegel (1986) used a stochastic process to model future profits and showed, by using option analogy, that the value of delaying an investment increases as uncertainty regarding future profit increases. McDonald and Siegel (1986) get the same results as Bernanke (1983) and Cukierman (1980) but their reasoning is different. Bernanke (1983) and Cukierman (1980) stress the value of accumulating information before proceeding while McDonald and Siegel (1986) refer to the increasing call option value as uncertainty of the underlying asset increases. In the wake of the paper by McDonald and Siegel (1986) follows a number of real option studies and several ways for valuing real option projects, many of which are summarized in textbooks such as Dixit and Pindyck (1994) and Trigeorgis (1996).

One paper of great relevance to our research is a study by Majd and Pindyck (1987) using real options for sequential investment decisions with time-to-build. They find, using contingent claims analysis[4], that the irreversible investment decisions can be very sensitive to the level of uncertainty. Investments under uncertainty, evaluated with the NPV method, may therefore result in overinvestments. Their results are in line with McDonald and Siegel (1986) and show that uncertainty is likely to have a depressive effect on investment spending. Majd and Pindyck (1987) also show that time-to-build is likely to increase this depressive effect. Milne and Whalley (2000) correct an error in Majd and Pindyck (1987) and find that longer time-to-build significantly reduces the effect uncertainty has on the optimal investment threshold and that NPV calculations could be an adequate method of evaluating projects with long time-to-build. Similar results are found by Bar-Ilan and Strange (1996, 1998) where they account for the opportunity cost of postponing investments by considering the forgone benefits of delaying investments when future news are good. This means that in addition to the call option, the firm possesses a valuable put option which increases in value as time-to-build gets larger. Bar-Ilan and Strange (1996) also argue that increased uncertainty in projects with long time-to-build could in some cases hasten the decision to invest. Bar-Ilan and Strange (1998) show that the entry level trigger price is lower than the second stage trigger price for a two-stage investment with suspension options and lags. These results offer parallels to learning-by-doing models such as that of Roberts and Weitzman (1981). Sødal (2006) corrects an error in Bar-Ilan and Strange (1996) and show that investment lags are likely to decrease the depressive effect of uncertainty and lower the entry level trigger price, but less so than argued in Bar-Ilan and Strange (1996)'s model.

## 2.2 Empirical

Several studies have examined whether real option theory gives a good approximation of real life investment behavior. Quigg (1993) finds empirical support for a model where market prices reflect a premium for the option to wait to invest in land development. In their empirical study, Moel and Tufano (2002) find that mine closures are influenced by the volatility and price of gold and that the real option model is a good descriptor of how flexibility is handled by mining companies. Bulan (2005) shows empirically that both increased industry and firm-specific uncertainty have a depressing effect on investments in the U.S. manufacturing sector. Dunne and Mu (2010) empirically model the investment process of U.S. oil refineries and show that increased uncertainty decreases the likelihood of refiner-

[4]Contingent claims analysis is a common method for valuing investment opportunities. The method assumes existence of spanning assets, i.e. traded assets that will exactly replicate the returns of the investment project (Dixit and Pindyck, 1994)

ies modifying their capacity.[5] These findings lend support to the irreversibility of investment decisions, accounted for in real option theory. Kellogg (2010) studies the Texas onshore oil drilling industry and finds that drilling activity responds to changes in oil price volatility with a magnitude that is consistent with real option theory. Slade (2013) finds evidence for the effect described by Bar-Ilan and Strange (1996, 1998) regarding how investment lags affect investment spending. She studies optimal investment timing under uncertainty with time-to-build in the copper mining industry from 1835 to 1986. Copper mines fit well into Bar-Ilan and Strange (1996)'s model as there are substantial investment lags and considerable copper price uncertainty. She finds that greater uncertainty encourages investment and lowers the price threshold when there is longer time to build. This is the opposite of the effect described in Majd and Pindyck (1987)'s theoretical model.

Authors that have investigated real option effects of regulatory uncertainty in electricity generation include, among others, Ishii and Yan (2011) and Fleten et al. (2012) . Ishii and Yan (2011) explore empirically the investment behavior of firms operating in the U.S. power sector under regulatory uncertainty from 1996 to 2000. They find a strong link between greater regulatory uncertainty and lesser investment spending, suggesting an option value that leads firms to postponing investments in power plants. Fleten et al. (2012) examine empirically the option to abandon, startup and shutdown existing power plants in the U.S. between 2001 and 2009. They find that regulatory uncertainty decreases the probability of shutting down operating plants and decreases the probability of starting up shutdown plants. These findings lend strong support to real option theory as higher uncertainty should decrease the probability of early exercise. These results are in line with our postponing results. We use a similar analytical approach as Fleten et al. (2012) in this paper.

## 2.3 U.S. Power Market Trends

As previously mentioned, our observation period include an interval with much restructuring activity. To put our results in context, and provide an explanation for several noteworthy phenomenons that may influence these, it is necessary to have an understanding of the dynamics of the U.S. Power market in the relevant years. Many of these events are connected with restructuring. Restructuring of the electricity generation market in the U.S. has been happening at the state level since

[5]Dunne and Mu (2010)'s main uncertainty measure is the daily forward refining margin spread, also referred to as the crack spread.

the mid-1990s and several states have been deregulated.[6] State level restructuring activities slowed down in the early 2000s and there has been little activity after this (EIA, 2014*b*).

One significant trend is described by Finon (2008), a wave of investments in combined cycle gas turbines in the late 1990s following deregulations. Independent power producers (IPPs)[7] relying on highly leveraged project financing agreements invested in merchant plants[8], without long-term contracts. Many of these projects went bankrupt in the early 2000s, as electricity prices fell and gas prices increased, causing spark spreads to decrease (Finon, 2008). This strongly affects our results since a large number of canceling and postponing observations are clustered in these years. Following the collapse of the merchant power market and reduced liquidity in the electricity forward market, the cost of capital for power companies increased as credit rating fell and risk preferences of financial players changed (Joskow, 2005). This made it difficult to obtain financing for merchant generators (Fraser, 2003). These observations are in line with Joskow (2005)'s note that the late 1990s boom turned into a bust with plentiful generating capacity available and many planned generators being canceled or postponed.

Another trend is described by Schubert et al. (2006), the introduction of competition moved the risk of capacity investment from the end users to the utilities. Market inefficiencies, most importantly price caps that ensure that the utilities cannot charge the scarcity value of energy in situations of periodic shortage, creates a "missing money problem" that is also described by Cramton and Stoft (2006); Joskow (2006); Rodilla and Batlle (2012), among others. This in turn creates a resource adequacy problem since the investment level will decrease until the number of days with capacity shortages is sufficiently large for the capped scarcity price to cover capital investments. This could mean that there will be a shift in the equilibrium reserve margin level.

Rodilla and Batlle (2012) argues that the restructuring process has actually increased the need for regulatory intervention to guarantee supply, Borenstein and Bushnell (2000) use the term "reregulation" to describe the same phenomenon. The missing money problem, lack of long term markets, and other market imperfections following the restructuring process have created a lasting state of market

[6] In this case the term "deregulation" refers to the implementation of retail and/ or wholesale competition, opening the market for new entry and moving the risk of investment in new generating capacity from the end user to the power producers. As we will see later in this section there will still be regulatory intervention in a "deregulated" state.

[7] An IPP is an owner of electricity generation facilities that is not a public utility.

[8] Merchant plant as described by Finon (2008): "A stand-alone producer that sells all the production on the short-term markets and without a long-term contract and develops its new capacities under project financing by non-recourse debt".

immaturity with continuous regulatory intervention (Rodilla and Batlle, 2012). As we try to measure regulatory uncertainty, this could possibly make this more challenging.

# 3 Context and Institutional Background

This section describes the data and variables used in the analysis. Primary data sources are the Energy Information Administration (EIA), U.S. Federal Reserve Bank (FED), wholesale electricity market system operators, North American Electric Reliability Corporation (NERC) and the Environmental Protection Agency (EPA).

Form 860, published each year by EIA, is our main source of raw data. The form collects data on the statuses of existing and proposed electric generators and associated equipment in the United States. We use this form to obtain the yearly status of all planned gas fueled combined cycle turbines and combustion turbines in the United States from 1990 until 2012.[9] The final dataset contains 37,821 generator-year observations for 3,748 individual generators, including all years each individual generator has had its status reported to the EIA. Of these generator-year observations, 9,886 observations are relevant for our regression analysis, as we are only looking at the generator-years when status changes occur or investment is delayed.

The data is analysed using two separate regression analyses. The *full sample* regression includes all the years we have data from EIA to calculate status changes and delayed investments, i.e. 1991 to 2011. This is the primary regression we will focus on in this thesis and its results are presented in Section 4. The spark spread standard deviation variable explained in Section 3.6 is excluded from this regression due to lack of wholesale price data. The second regression is the *spark spread sample* regression presented in Section 5 containing data from the years 2003 to 2011. This regression includes the spark spread standard deviation variable, see Section 3.6, but omits the PCAP variable explained in Section 3.8. The definition of the spark spread variable differ in the two regressions, as is discussed in Section 3.6 and 3.7.

## 3.1 Generators

Our analysis assesses proposed combined cycle turbines fueled by natural gas (CCGTs) and proposed gas fueled combustion turbines (GTs). The respective prime mover[10] codes for these generators in Form 860 are described in Table 1.

[9]Except from generators planned in the states of Hawaii and Alaska.

[10]A prime mover is a machine or mechanism that converts natural energy into work. In our case, this machine is the turbine. We use the words generator and turbine interchangeably in this paper.

*Table 1: Explanation of different prime mover codes for combined cycle turbines in Form 860*

| Code | Description | Explanation |
|---|---|---|
| CC | Combined cycle total unit | Used only in planning stage, when specific generator details cannot be provided |
| CA | CC steam turbine part | |
| CT | CC combustion turbine part | |
| CS | Combined cycle single shaft | Combustion turbine and steam turbine share a single generator |
| GT | Combustion (gas) turbine | |

The heat rate data is gathered from EPA's continuous emission monitoring system (CEMS) data. CEMS only contains data for the whole combined cycle turbine, not for the individual steam or combustion part, which makes it necessary to merge the two parts. We have merged the capacity of the steam turbine part and the combustion turbine part of the same generator found in Form 860 and named them CCs (Combine Cycle Turbines) in our final dataset. This is done in order to correctly merge the EIA data together with the data used to calculate heat rates for each generator.[11]

The principle of a combined cycle gas plant is to use the exhaust from burning natural gas in one or more combustion turbines to power one or more steam turbines. The use of the otherwise wasted heat in the turbine exhaust gas results in higher efficiency, lower flexibility and higher capital costs compared to simple cycle combustion turbines. The combined cycle plants are usually used as intermediate or peak load while combustion turbines are mainly used as peak load. Demand spikes are handled by intermediate and peak load plants and the intermediate load combined cycle plants usually are dispatched at a lower electricity price than simple cycle combustion turbines due to their higher efficiency.

## 3.2 Status Changes

Each year almost every power company in the United States reports the status of proposed generators to the EIA via Form 860. For predefined stages of a sequential investment process, each generator is accounted for using a status code, see Table 2. This code is the key variable of our research, as it reveals investment decisions made each year.

[11]It is possible to merge the two datasets because of identical plant codes in EIA form 860 and the CEMS data.

*Table 2: Explanation of relevant status codes in Form 860 as of 2012. Each status code represents a stage in a sequential investment except from IP, which represent a cancellation of an investment*

| 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 |

The definitions of the various status codes are not constant from 1990 until 2012. Therefore we have made the necessary changes to the status definitions in order to make them constant over time. The statuses are defined as in Table 3 in our final data. The number of transitions made between the different investment stages are outlined in Figure 5 and Figure 6 in the Appendix A.1.

*Table 3: Simplified status codes used in our regression analysis*

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

At all times, a company planning to build a new generator has three choices; it can proceed, postpone or cancel the sequential investment process. We have EIA Form 860 data from 1990 to 2012. The decision the company makes in year $t$ will be reported in EIA Form 860 in year $t + 1$. This is why we look at generator decisions from 1991[12] to 2011 when we analyse our full sample data, as the newest data available is EIA Form 860 from 2012 and the decisions registered in that form were made in 2011.

We define the investment process as postponed if a generator is stuck with the same status code for more than one year. The exception is time spent in status code

[12] The reason why we look at the decisions from 1991 and not 1990, is because of the timing issues of the independent variables mentioned in Section 3.4. We do not have the necessary data from 1989 in order to calculate the independent variables we need to analyse the 1990 decisions.

three (U) because of time-to-build. The estimated average lead time is three years for a combined cycle generator and two years for a gas combustion generator (EIA, 2009).[13] Therefore we do not consider a generator postponed in the building phase until the time spent in status U exceeds three years for combined cycle turbines and two years for combustion turbines. Conversely, an investment is considered to be proceeding if the status moves forward to a more advanced stage in the following year or if a generator does not stay more than three years for combined cycle turbines and two years for combustion turbines in building stage as explained above. Canceling is moving from any of the planning stages in year $t$ to cancelled in year $t+1$. Figure 1 illustrates the occurrences of the three investment decisions for each year.

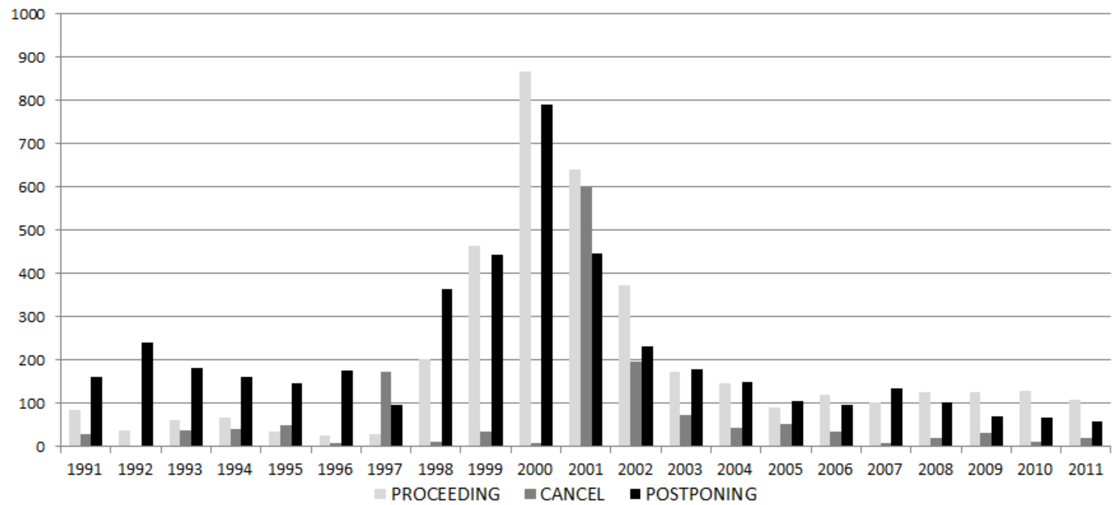



*Figure 1: Occurrences of the three different investment decisions by year from 1991 to 2011. The abnormally high activity in the years 1998-2002 are explained in Section 3.3.*

## 3.3 Trends

As noted in Section 1 there was a wave of IPP investments in the late 1990s that was followed by a collapse. This is visible in Figure 1. There is much activity, especially in the form of proceedings, but also postponings in the years 1998 to 2002. In 2001 and 2002 there is also a large number of cancelings as the bubble collapsed. This abnormal activity level following a period of deregulation and expectations for further deregulation is a challenge for our analysis. 62.9 % of

[13]These average lead times does not change over the time period from 1997 to 2012 according to the EIA, we assume the lead times to be equal to these numbers also before 1997.

our proceeding observations are from the 1998 to 2002 period, with 50.2 % of the postponing and 56.6 % of the canceling observations from the same period. For canceling 52.9 % of the observations are from 2001 and 2002. To control for this we have created a variable called PCAP that is described in section 3.8.

## 3.4 Timing Issues of Independent Variables

When considering how the independent variables affect the investment decision of a generator owner we need to look at the data available at the time the decision was made. We make the conservative assumption that the external data affecting the decision in year $t$, revealed in year $t+1$, is not yet available for year $t$. We therefore look at how the external data of year $t-1$ affect the decisions in year $t$. Not all the variables are defined in this way. The variables that account for the size of the generators and the number of generators owned by each firm are not backward looking as we assume this information is available by the decision makers in the year each decision is made. The same goes for the regulatory uncertainty variable. The different independent variables are defined in the following subsections.

## 3.5 Regulatory Uncertainty

The effect of regulatory uncertainty on electricity generation investment have been examined by several authors, among others Ishii and Yan (2011); Fleten et al. (2012); Fabrizio (2013). Still there exists no standard measure of regulatory uncertainty. Most authors use binary indicator variables based on qualitative information. Fabrizio (2013) investigates investment in renewable electricity generation assets in states that have enacted Renewable Portfolio Standard (RPS) policies. As a proxy for regulatory uncertainty she uses the state's history of regulatory stability in electricity industry restructuring. Specifically, she defines states that have enacted and repealed deregulation legislation as states with regulatory uncertainty. Fleten et al. (2012) uses descriptive data from EIA and the fact that the process in which competition is implemented has a distinct sequence to develop a retail competition index, to identify the regulatory status of the individual states, as in Table 4. For the purpose of proxying uncertainty they use a binary variable that is equal to one for values of the index consistent with regulatory uncertainty and zero otherwise. Ishii and Yan (2011) use the timing for passing of restructuring legislation to create three binary regulatory uncertainty variables that are equal to one respectively one, two and three years before the passing of legislation. The intuition behind this is that power companies follow the restructuring process and should be fairly sure if there is an imminent regulatory shift. Two or three years away from the decision however, they should experience more uncertainty as the outcome most likely will not be certain. They also do a structural analysis where they create a state level transition probability variable. This variable takes into consideration the retail price in the state at the start of the observation period.

*Table 4: Explanation of index values in the regulatory uncertainty index*

| Index value | Description |
|---|---|
| 1 | No activity |
| 2 | Investigation underway |
| 3 | Competition recommended |
| 4 | Law passed requiring retail competition |
| 5 | Competition implemented. |

The aforementioned papers use very different assumptions and methodology in their attempts at capturing the effects of regulatory uncertainty. Ishii and Yan (2011) focus on the timing of regulatory changes as they assume that restructuring was considered inevitable. Fabrizio (2013) on the other hand focus on the stability of the regulatory changes and past changes that have been repealed. Fleten et al. (2012) uses the typical regulatory process with an investigation preceding any legislation to pinpoint the years where options are being evaluated and the outcome of the process hence will seem uncertain. We have chosen a similar approach to Fleten et al. (2012), as we find the EIA descriptive data to gives a good overview of the regulatory process in each state. The timeline vary considerably from state to state, and we therefore believe that it is advantageous to try to create a variable that fits the specifics of each state, as an alternative to making assumptions about the duration of the process. Still, there are some factors that may not be captured by using this source alone. Because of this we also include filters to account for differences in low price states and the general uncertainty of the late 1990s. The methodology is described below.

For our regulatory uncertainty variable we use the retail competition index defined by Fleten et al. (2012) and Delmas and Tokat (2005) to create a binary indicator variable we call REGUNCERT. Referring to the retail competition index, in a state with an index number of two there is uncertainty regarding the introduction of competition. In a state where the index is three, there is uncertainty regarding the final form of the competition. Therefore the REGUNCERT variable is equal to one for retail competition index values of two and three and equal to zero otherwise. It is possible for states to move backwards on the regulatory uncertainty index.[14] Even though we use the index defined by Fleten et al. (2012), all of the variable

[14] Examples of this include California in 2000/2001 and Arizona in 2003/2004

entries may not be the same as we have evaluated the data from EIA (2014*b*) ourselves.

In addition to this we also assume that many industry participants believed that electricity restructuring was inevitable before the California energy crisis (Ishii and Yan, 2011). Specifically we make the REGUNCERT variable equal to one in regulated states in the years from 1996, when the restructuring in California really started to move forward, to 2000 when the electricity prices in California skyrocketed and there were rolling blackouts in the San Francisco area EIA (2000). The California energy crisis in 2000 and the collapse of Enron in 2001 challenged the deregulation trend and restructuring activity was to a large degree halted after this (Duane, 2002; Fabrizio, 2013).

Differences in power prices between states have been a motivation for advocates for expanded restructuring (EIA, 2000; Ishii and Yan, 2011). It seems reasonable that states with a relatively high price level will have more incentive to implement regulatory changes. The unknown timing and form of these changes can create an environment of regulatory uncertainty. We use data on yearly average electricity prices from EIA to rank the states from high to low each year. States that consistently end up among the 25 % with the lowest prices, and have little regulatory activity as described by EIA, are defined as having no regulatory uncertainty with a REGUNCERT value of zero. When deciding whether a low price state qualifies as a state with little regulatory activity, we use data from EIA (2014*b*), as we did when building the regulatory uncertainty index. This determination process could be seen as problematic as it will be a subjective qualitative exercise. To investigate whether our evaluating what can be considered little regulatory activity creates unusual results, we create a version of the variable without the low price filter. For the results in sections 4 and 5, the effects have the same signs and significance levels, the marginal effects only slightly change. The possibly controversial evaluation is therefore not an issue in this paper. That said, interpretation will always be a factor as we have chosen to use descriptive data to build the variable, and the values could always be challenged.

By using the EIA descriptive data in combination with the assumption that there existed a general regulatory uncertainty in regulated states in the U.S. between 1996 and 2000, except from in low price states with little regulatory activity, we try to create a variable that capture as many aspects of the complex dynamics of the electricity restructuring as practically possible. As there is no standard measure, we believe that this hybrid version might capture regulatory uncertainty in an advantageous way. The values our regulatory uncertainty variable takes in the different U.S. states from 1990 to 2011 are outlined in Figure 13 in Appendix A.4.

Regulatory change may yield both positive and negative effects for power producers, dependent on among other things, their relative cost positions and the prevalence of the missing money problem in the state, see Section 1. Deregulation moves the risk of adding new capacity from the consumer to the power producers, hence changing the incentives to invest (Finon, 2008; Wangensteen, 2011). According to real option theory, increased uncertainty of future profits should increase the value of delaying the investment in order to gather more information. We expect regulatory uncertainty to have this effect on the decision to postpone an investment. The effect of regulatory uncertainty on cancellation should be ambiguous as it is determined by each individual company's outlook to regulatory change. Some firms will benefit from the deregulation and others will have to cancel because of the expected increase in competition.

## 3.6 Spark Spread and Spark Spread Standard Deviation

The spark spread standard deviation variable is not included in the full sample regression, but is presented as an integral part of the spark spread sample regression in Section 5. The spark spread presented here is only used in the spark spread sample regression, see Section 3.7 for the spark spread variable used in the full sample regression.

Electricity prices in the U.S. are strongly dependent on natural gas prices. This is because natural gas plants usually are being dispatched last to meet electricity demand, historically due to high gas prices and the flexibility of gas-fired plants.[15] Hence marginal pricing of electricity when gas is on margin is largely decided by the marginal gas price.[16] The high correlation between electricity and gas prices during certain periods makes the two prices unsuitable on a stand-alone basis when valuing generators.

The spark spread is a common metric for estimating the profitability of gas-fired generators, and it gives a better picture of market conditions than electricity or gas prices alone. Additionally, using the spark spread simplifies the analysis of investment decisions from a two-dimensional to a one-dimensional problem (Näsäkkäla and Fleten, 2005). The spark spread is defined as the difference between the price received for electricity production and the cost of burning the natural gas needed for the generation of that electricity (Näsäkkäla and Fleten, 2005). We expect a higher spark spread to have a negative effect on investors decision to postpone and cancel a planned generator as this variable indicates higher profitability for the proposed power plant. The daily spark spread is given by:

[15] At very high prices the marginal fuel is oil, which is even more expensive than gas

[16] Other factors that determine electricity prices are the level of customer load, the seasonal variation of load, supplier risks and other non-energy costs

$$SPRD_{ik,n} = P_{k,n}^{elec} - HR_i \times P_n^{gas} \tag{1}$$

| | | |
|---|---|---|
| $SPRD_{ik,n}$ | $[\frac{\$}{MWh}]$ | is the spark spread for generator $i$, in region $k$, on day $n$ |
| $P_{k,n}^{elec}$ | $[\frac{\$}{MWh}]$ | is the day-ahead electric price in region $k$ on day $n$ |
| $HR_i$ | $[\frac{MMBtu}{MWh}]$ | is the generator $i$ heat rate (measure of efficiency) |
| $P_{k,n}^{gas}$ | $[\frac{\$}{MMBtu}]$ | is the price of gas on day $n$ |

The yearly average spark spread, the variable used in the spark spread sample regression, is given by:

$$\overline{SPRD}_{ik,t-1} = \frac{1}{N_{k,t-1}} \sum_{n=1}^{365} SPRD_{ik,n} \bigg|_{t-1} \tag{2}$$

| | | |
|---|---|---|
| $\overline{SPRD}_{ik,t-1}$ | $[\frac{\$}{MWh}]$ | is the average spark spread for generator $i$ in region $k$ in year $t-1$ |
| $SPRD_{ik,n}$ | $[\frac{\$}{MWh}]$ | is the spark spread for generator $i$, in region $k$, on day $n$ |
| $N_{k,t-1}$ | | is the number of days with available daily gas and electricity price data for region $k$ in year $t-1$ |

We define the cost of production as the product of the generators heat rate and the gas price; we ignore other costs and assume spark spread to be the variable component of marginal profit.[17] The heat rate is defined as the number of British Thermal units (BTUs) required to produce one Watt hour (Wh). It can be thought of as an inverse efficiency measure as a lower heat rate leads to higher efficiency.[18] Daily spot prices for NYMEX Henry Hub natural gas are taken from the EIA website, day-ahead electricity prices are taken from the respective sources referred to in Table 5. Daily wholesale electricity prices going all the way back to 1990 do not exist for any of the U.S. states included in this research. Therefore we use what prices are available and create the spark spread variable which we use to calculate the spark spread standard deviation variable, in order to look at the effect profitability uncertainty has on investments. We have enough price data to run the spark spread sample regression on these variables from 2003 to 2011.

[17]Marginal cost effects from emission-, distribution-, maintenance- and other operational costs are excluded, and the spark spread is therefore not an exact measure of profitability, but rather an indicator of market conditions.

[18]MMBtu and MWh is related by a scale factor, 3.41275 MMBtu are equivalent to one MWh. Thus the energy conversion efficiency can be calculated as $\eta = \frac{P_{out}}{P_{in}} = \frac{3.41275 \frac{MMBtu}{MWh}}{HR \frac{MMBtu}{MWh}}$

*Table 5: Price data used in order to calculate spark spread. Due to timing issues, see Section 3.4, we need data from 2002 to 2010 in order to account for the investment decisions happening from 2003 to 2011. Most prices are gathered from EIA (2014a).*

| Region | Years included | Source |
|---|---|---|
| NYISO[19] | 2002-2010 | NYISO wepage |
| ISO-NE[19] | 2002-2010 | ISO-NE webpage |
| PJM | 2002-2010 | PJM webpage |
| MISO | 2006-2010 | MISO webpage |
| CAISO | 2002-2010 | EIA webpage |
| ERCOT | 2002-2010 | EIA webpage |
| SERC[20] | 2002-2010 | EIA webpage |
| SOUTHWEST[20] | 2002-2010 | EIA webpage |
| NORTHWEST[20] | 2002-2010 | EIA webpage |

The calculated spark spread is not an observed value, it is constructed as a representation of what the spark spread would have been had the proposed generator been operating. We ignore the marginal increase in electricity supply and gas demand due to adding one more combined cycle generator to the supply mix, as we assume it is negligible compared to the total load when calculating the spark spread for each individual generator. We define our regression variable used in the spark spread sample regression as the standard deviation of last year's spark spread:

$$SPRDSD_{ik,t-1} = \sqrt{\frac{1}{N}\sum_{n=1}^{N_{k,t-1}} [SPRD_{ik,n} - \overline{SPRD}_{ik}]^2}\Bigg|_{t-1} \tag{3}$$

| | |
|---|---|
| $SPRDSD_{ik,t-1}$ | is the standard deviation of the spark spread for generator $i$, in region $k$, in year $t-1$ |
| $SPRD_{ik,n}$ | is the spark spread for generator $i$, in region $k$, on day $n$ in year $t-1$ |
| $\overline{SPRD}_{ik,t-1}$ | is the average spark spread for generator $i$ in region $k$ in year $t-1$ |
| $N_{k,t-1}$ | is the number of days with available daily gas and electricity price data for region $k$ in year $t-1$ |

For financial call options, higher volatility of the underlying asset increases the option value and raises the optimal early exercise boundary price, thus creating

[19] For ISO-NE and NYISO we use real time spot prices not day-ahead prices.

[20] SOUTHWEST prices are calculated using Palo Verde hub prices, NORTHWEST prices are calculated using Mid-Colombia hub prices and SERC prices are calculated using Entergy hub prices. States are linked to the specific regions using maps from FERC (2014).

incentives to delay investments (McDonald, 2006). The effect of uncertainty becomes ambiguous when considering real options on power plants with the ability to ramp up and down the level of electricity production, as is the case for both peak load plants and intermediate load plants (Näsäkkäla and Fleten, 2005). We explain the two effects as follows:

1. Higher spark spread volatility increases the value of flexible plants with the ability to ramp up and down production, hence encouraging these plants to proceed with their investments in order to capitalize on the production opportunities created by high uncertainty. We refer to this effect as the *flexibility effect*.

2. As for financial call options, higher spark spread volatility should delay early exercise of the investment, hence creating an incentive to postpone the investment and wait for more information. We refer to this effect as the *call option effect*.

Peak load plants should be affected more by the flexibility effect compared to intermediate load plants due to their higher production flexibility. Base load plants are unaffected by this effect due to their inability of ramping up and down production. Intermediate load plants and even more so, base load plants, should be more affected by the call option effect compared to peak load plants because longer time-to-build is believed to increase the depressive effect uncertainty has on investment spending (Majd and Pindyck, 1987).[21] Investments in the larger intermediate and base load plants are considered more irreversible than the peak load plant investments; this should also magnify the call option effect for intermediate load plants compared to peak load plants. The ambiguous effects created by the spark spread standard deviation on investments in flexible power plants should therefore cause intermediate load plants to postpone their decisions more often than peak load plants under profitability uncertainty. We also expect intermediate load plants to be more likely to cancel investments relative to peak load plants during times of high spark spread standard deviation due to the flexibility effect. It is hard to tell which of the two effects will act the strongest on the generators in our dataset as it consists of both intermediate and peak load plants. In Section 5 we test the effect of spark spread standard deviation on intermediate and peak load plants individually.

[21] This argument might not hold as shown by Milne and Whalley (2000) and Bar-Ilan and Strange (1996, 1998), see Section 1 for a theoretical discussion regarding this issue.

## 3.7 Spark Spread Approximation

This variable is created in order to have a representation of generator profitability in the full sample regression. Spark spread is already defined in Equation (1) using daily wholesale electricity data. The daily wholesale price data is not available for all the years from 1990 to 2010.

We approximate an equivalent spark spread profitability variable based on state level annual retail electricity prices gathered from EIA, Henry Hub natural gas prices from Reuters and the generators specific heat rates from CEMS and EIA Form 860. The development of annual retail electricity prices for each U.S. state and the annual Henry Hub prices are illustrated in Figure 9 and Figure 8 respectively in Appendix A.2. We call this regression variable RHH and it is given by:

$$RHH_{is,t-1} = \frac{P^{elec}_{s,t-1}}{100\frac{¢}{\$}} \times 1000\frac{MWh}{kWh} - HR_i \times P^{gas}_{t-1} \tag{4}$$

| | | |
|---|---|---|
| $RHH_{is,t-1}$ | $[\frac{\$}{kWh}]$ | is the spark spread for generator $i$, in state $s$, in year $t-1$ |
| $P^{elec}_{s,t-1}$ | $[\frac{¢}{kWh}]$[22] | is annual retail electricity price in state $s$, in year $t-1$ |
| $HR_i$ | $[\frac{MMBtu}{MWh}]$ | is the generator $i$ heat rate (inverse measure of efficiency) |
| $P^{gas}_{t-1}$ | $[\frac{\$}{MMBtu}]$ | is the annual Henry Hub natural gas price in year $t-1$ |

We expect this variable to effect investment decisions in the same way the variable constructed with Equation (1) does; a higher spark spread variable indicates greater profitability hence has a negative effect on investors decision to postpone or cancel a planned generator.

## 3.8 Macroeconomic Factors

In this section we present the variables that are related to the economic environment.

### Relative Planned Capacity

The collapse of the merchant market, as described in Section 1 and 3.3, is visible in our dataset. To control for the trend we create a variable by calculating the ratio

[22]Retail prices from EIA are quoted in ¢ per kWh.

of planned capacity to installed capacity on the state level using installed capacity data from EIA and planned capacity data from EIA Form 860. This variable is only used in the full sample regression as the collapse of the merchant market is outside the time frame of the spark spread sample regression. This variable is named PCAP and is given by:

$$PCAP_{s,t-1} = \frac{PLANCAP_{s,t-1}}{ICAP_{s,t-1}} \tag{5}$$

| | |
|---|---|
| $PCAP_{s,t-1}$ | is the relative planned capacity in state $s$, in year $t-1$ |
| $PLANCAP_{s,t-1}$ | is the planned new additional capacity in state $s$, in year $t-1$ |
| $ICAP_{s,t-1}$ | is the installed capacity in state $s$, in year $t-1$ |

High PCAP values indicates high levels of investment activity and could potentially predict bubbles, such as the investment bubble prior to the merchant market collapse, see Section 3.3. We expect it to have a positive effect on canceling, due to the fact that canceling takes place in large numbers following the burst of the bubble. It could be argued that the variable should have an ambiguous effect as a bubble may last for several years, while a collapse could be quick. In this scenario there would be many years with a high PCAP, positive investment climate and little canceling, before the collapse and matching rush of canceling. We also see this in our data and the variable is not ideal. Still, a collapse will typically follow the peak, so the highest levels of planned capacity, should precede the highest levels of canceling. We believe that the variable could control for the collapse of the merchant market in a satisfactory way, and hence it should work for this particular trend, which is the intension of the variable. Also, even though it might be argued that the sign of the effect is not completely clear cut, the variable captures the activity level in a direct way. This is equally important when faced with phenomenon such as the collapse of the merchant market.

When comparing postponing to proceeding we expect the relative level of planned capacity to have a negative effect. Even though there will be more postponing with a higher activity level, we believe that there will be a relatively higher increase in proceedings in a positive investment climate as investors rush to invest. When there is a market collapse, postponing may not be a natural reaction as the collapse can provide new information that undermines the assumptions made in the initial investment analysis and makes canceling the preferred approach. Also, in cases where the owner goes bankrupt, canceling may be the only alternative. Figure 2 illustrate of how this variable varies on a national level.

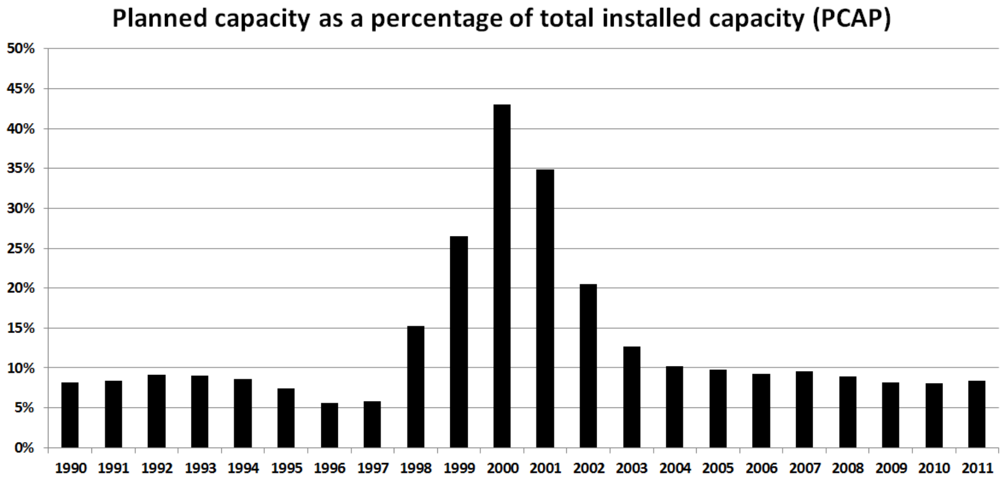



*Figure 2: PCAP: The figure gives the actual total planned capacity for the U.S. divided by the total installed capacity in year $t$. In the regressions we use state level PCAP, the graphic representaion of this can be found in Figure 12 in Appendix A.3. The obvious jump in the years 1998 to 2002 coincide with the IPP investment bubble and collapse of the merchant market as described in Section 1 and 3.3*

The level of planned capacity will naturally depend upon the amount of proposed generators getting canceled and the number of planned generators that turn in to operating generators, affecting the level of installed capacity. This raises the question whether the relative planned capacity variable is endogenous.[23] This should not be a problem in our case as the planned capacity variable is backward looking as explained in Section 3.4. The causality loop is not a closed loop because we look at the lagged value of relative planned capacity. The relative planned capacity in year $t-1$ will impact cancellations and proceedings in year $t$. The cancellations and proceedings in year $t$ will in turn impact the level of planned capacity in year $t$ but not in year $t-1$.

### Interest Rates

We use the risk free, ten-year U.S. Treasury note interest rate to investigate the relationship between interest levels and investment decisions. Interest rates are gathered from FED and its development is illustrated in Figure 7 in Appendix A.2. We define the $T10$ regression variable in year $t$ as the observed $T10$ interest rate

[23]Endogeneity occurs when there is correlation between an independent variable and the error term in a model. Endogeneity can be defined as a causality loop between the independent and dependent variable in a regression model i.e., X causes Y but Y also causes X.

in year $t-1$.

$$T10_{t-1} \tag{6}$$

| | |
|---|---|
| $T10_{t-1}$ | is the year $t-1$ average ten-year U.S. treasury note interest rate (rated AAA) |

We expect higher interest rates to have a positive effect on investors' willingness to cancel or postpone investments. Higher rates will increase opportunity cost of investing and cost of capital hence discouraging early exercise and reducing investment (Dixit and Pindyck, 1994).

Referring to Figure 7 in Appendix A.2 it is obvious that the interest rate has a negative trend in the observation period, and it visually appears to be non-stationary.[24] It could be argued that it has a similar effect as a negative time variable. We assume that the interest rate is a stationary variable, with our sample not being large enough for this to be obvious. We also assume that the interest rate gives a good approximation for the cost of capital. With these assumptions, a reduction in the interest level should yield relevant effects and the stationary issue should not be a concern.

### Reserve Margin

Demand for electricity fluctuates throughout the day. Since there currently are no economically viable alternatives for storing large quantities of electricity, there needs to be enough generating capacity to cover situations of high demand (Wangensteen, 2011). To ensure this supply sufficiency there is a structure of base load, intermediate load and peak load plants that produce at different levels of demand, see Figure 3. Higher reserve margins will have a negative effect on the electricity price (Fleten et al., 2012) and might because of this impact investment decisions. We expect a higher reserve margin to lead to a more postponing and canceling of investments as higher reserve margins means increased electricity supply which in turn creates decreasing electricity prices.

The equilibrium reserve margin in each area will be influenced by the load structure and regulations such as price caps (Finon, 2008).

[24] Stationarity means that the variable's probability distribution is constant over time. Consequently, parameters like variance and mean are constant over time. One runs the risk of obtaining spurious regression results by including non-stationary independent variables.

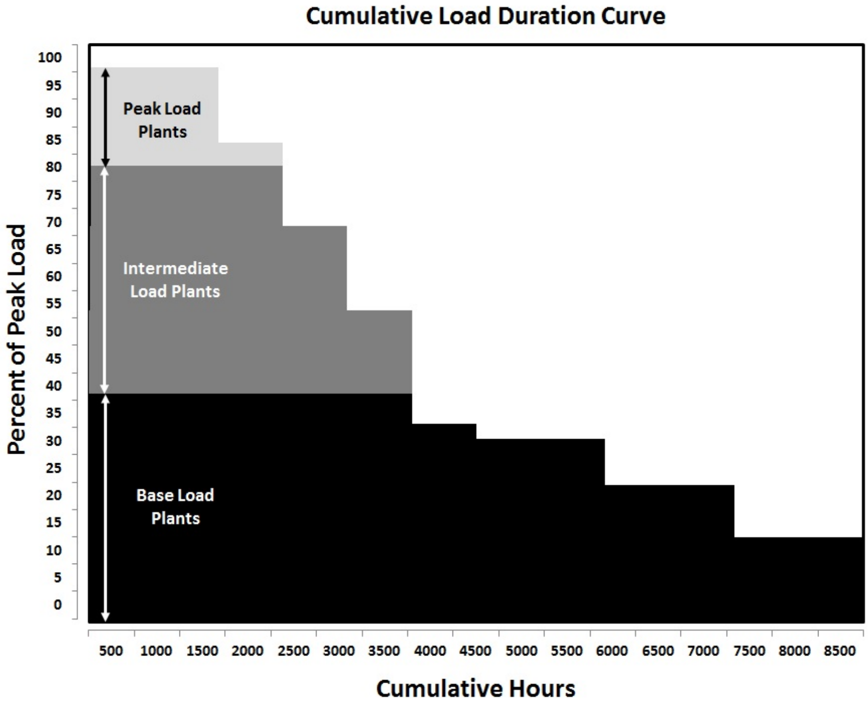



*Figure 3: Load pyramid, created for illustration purposes. Double arrows indicate relative share of load distribution for each load category: Base, Intermediate and Peak*

Reserve margin is defined to be the difference between the available installed capacity and the forecasted peak demand.

$$RM_{k,t} = \frac{(C_{k,t} - D_{k,t})}{D_{k,t}} \tag{7}$$

| | |
|---|---|
| $RM_{k,t}$ | is the year $t$ reserve margin for region $k$ |
| $C_{k,t}$ | is the year $t$ capacity in region $k$ |
| $D_{k,t}$ | is the year $t$ peak demand in region $k$ |

Capacity and demand data are taken from from North American Electric Reliability Corporation's electricity supply and demand database, the data is structured into regions. The definition of the boundaries of these NERC regions have changed twice between 1990 and 2012 as illustrated by Figure 11 in the Appendix A.2. These changes are accounted for in our reserve margin calculations. The supply and demand database is based on official EIA filings, and the projections in the database are aggregated from the plans of capacity additions and retirements as well as projections for demand of the individual power plants. The projections thus come from the power plants themselves.

The newest data a decision maker in year $t$ will have access to is the data published in year $t-1$. Therefore we use data from the supply and demand database published in year $t-1$ when analysing decisions made in year $t$. The NERC data is structured in such a way that the supply and demand data published in year $t-1$ contains actual data for year $t-2$ as well as predictions of supply and demand data for years $t-1$ through $t+8$. The best estimate of year $t$ reserve margin a decision maker then can obtain in year $t$ is the year $t$ reserve margin that was predicted by the NERC data published in year $t-1$. Figure 10 in Appendix A.2 show how the reserve margin variable for the different NERC regions have developed from 1990 to 2010. We define the variable as:

$$RM_{k,t-1}^{pred(+1y)} \tag{8}$$

| | |
|---|---|
| $RM_{k,t-1}^{pred(+1y)}$ | is the reserve margin prediction made in the year $t-1$ electricity supply and demand database for year $t$ reserve margin in region $k$ |

The supply and demand database is publicly available and we assume decision makers to some degree use these estimates when evaluating investment opportunities in the different regions. Projections are not always the equivalent of actual outcomes, which is also the case for the forward looking reserve margin estimates provided by the North American Electric Reliability Corporation. We calculate the absolute value of the difference between the predicted reserve margin and the actual reserve margin revealed by NERC two years later. The average estimation error for all relevant regions and years is 4.5 percent points. We think this error is relatively high as the average reserve margin over the same sample is 14.8 % with a standard deviation of 5.8 %. Still, these estimates are what is available and even though they do not precisely predict the future, they provide an indication of the reserve margin expected by the market.

## 3.9 Firm Specific Factors

### Firm Size and Generator Size

Large firms will on average be more diversified and have larger opportunity to subsidize less profitable plants (Moel and Tufano, 2002). These reasons arise from having a greater likelihood of presence in different geographical regions and of being vertically or horizontally integrated. Large firms will also experience economies of scale, have access to more expertise and have the option of moving resources from one plant to another, giving these companies more flexibility in their decisions. As a measure of firm size, we use the variable TG, the total number of existing operating generators owned by the firm.[25] As described in Section 1 the collapse of the merchant power market in the early 2000s led to a wave of canceling and postponing, and since this was primarily an IPP bubble, it should support the expectation that large companies proceed more.

Power producers face the trade-off between investing in large plants with low costs per unit, or adding capacity in smaller amounts more frequently at a higher cost per unit. Uncertainty over future demand should influence how companies evaluates the trade-offs between scale and flexibility (Dixit and Pindyck, 1994). Different sized generators may also be subject to different market conditions and economies, given that they may have different places in the load hierarchy. We investigate how the capacity size of a planned generator influences investment decisions. For this we use the variable SIZE, which measures the summer capacity of each generator in Megawatt (MW).

[25] An alternative measure could have been the total installed capacity

## 3.10 Summary of Expected Effects of Independent Variables

As noted by Dixit and Pindyck (1994), it is important to be careful when evaluating the effects of individual variables as these are unlikely to be independent of each other. An example of this might be the risk free interest rate. A higher risk free rate should when evaluated in isolation depress investment. However, a positive change in the interest rates may coincide with economic growth that may simultaneously change the expected demand and hence the reserve margin, making the individual effects difficult to interpret. Table 6 presents a summary of the expected stand-alone marginal effect for each independent variable on the various investment decisions.

*Table 6: The table presents a summary of the expected marginal effect of each variable on the different decisions as well as a reason for why we expect this effect. The expected sign of the marginal effect is given in parentheses for each variable and decision. A plus sign predicts a positive marginal effect and a minus sign predicts a negative marginal effect.*

<table>
<tr><th></th><th colspan="2">Sign of expected marginal effect & explanation of prediction</th></tr>
<tr><th>Variable</th><th>Postpone(1) vs. Proceed(0)</th><th>Cancel(1) vs. Proceed(0)</th></tr>
<tr><td>REGUNCERT</td><td>(+) According to real option theory increased uncertainty of future profits should increase the value of delaying the investment in order to gather more information.</td><td>(+/-)We expect regulatory uncertainty producers to have an ambiguous effect on the decision to cancel vs. the decision to proceed. The effect will be determined by each company's outlook to regulatory change. E.g. cost benefits or the missing money problem will determine this.</td></tr>
<tr><td>SPRDSD</td><td>(+/-) Higher profitability uncertainty raises the early exercise boundary value. However, the variable has ambiguous effects on peak- and intermediate load plants (See Section 3.6).</td><td>(-) Higher price uncertainty is beneficial for power plants with the option to ramp up and down their electricity production, discouraging cancellation.</td></tr>
<tr><td>T10</td><td>(+) Higher interest rates will increase the opportunity cost of investing hence discourage early exercise.</td><td>(+) Higher interest rate increases the cost of capital, reducing investment.</td></tr>
<tr><td>PCAP</td><td>(-) A high activity level should motivate more proceeding, and canceling if there is a bubble. Higher PCAP should hence give less postponing.</td><td>(+) Investors should be prone to cancel their investments if too many generators are being planned in a region. A high PCAP should because of this give more canceling.</td></tr>
<tr><td>RM</td><td>(+) Higher reserve margin implies lower profitability, decreasing the value of the underlying investment, thus decreasing the opportunity cost of delaying the project and discouraging early exercise.</td><td>(+) An increase in available generating capacity increases supply, hence decreasing electricity prices and encouraging cancellation.</td></tr>
<tr><td>RHH/SPRD</td><td colspan="2">(-) A higher spark spread indicates higher profitability for the proposed generator thus discouraging postponing and cancellation of planned capacity</td></tr>
<tr><td>TG</td><td colspan="2">(-) Larger firms have the benefits of economies of scale and are more diversified. These effects should increase the probability of proceeding.</td></tr>
<tr><td>SIZE</td><td colspan="2">(+/-) How size effects investment decisions should depend on uncertainty of future demand, this level of uncertainty will decide whether investors prefer scale or flexibility. As we make no assumptions for future uncertainty, we believe size will have an ambiguous effect.</td></tr>
</table>

# 4 Full Sample Regression

In this section we use the full sample regression to analyse how the variables presented in Section 3 affect the decision to postpone, proceed or cancel a sequential investment in gas fired combined cycle and combustion turbines. We study the decisions individually in individual logistic regressions and study all the variables together by performing a multivariate logistic regression. We end the section with a short look at a multinomial regression with respect to both the cancel and postponing variables.

## 4.1 Decisions to Postpone: Full Sample Regression

Here we investigate the factors that affect a firm's decision to postpone a planned investment. We have a total of 8,403 relevant generator-year observations, of which 4,399 generators were postponed and 4,004 generators proceeded with the investment. Multicollinearity is not an issue in the full sample postponing regression as the correlations between the independent variables are low. A Hosmer-Lemeshow test for the postponing regression confirms that the model fits the data and the receiver operating curve tells us that the model is more likely to correctly predict investment behavior than a random model. All these statistic test results are discussed in detail in Appendix B. The individual and multivariate regressions are presented in Table 7.

### 4.1.1 Individual and Multivariate Regressions

We use the multivariate logistic regression in Equation (9) to analyse decisions to postpone. See Appendix B.1 for an explanation of the logistic regression and how the regression results can be interpreted.

$$\begin{aligned} DV_{i,t}^{postponing} &= F(\beta_0 + (\beta_1 \times REGUNCERT_{s,t}) + (\beta_2 \times T10_{t-1}) \\ &+ (\beta_3 \times PCAP_{s,t-1}) + (\beta_4 \times RM_{k,t-1}^{pred(+1y)}) + (\beta_5 \times RHH_{is,t-1}) \\ &+ (\beta_6 \times TG_{i,t}) + (\beta_7 \times SIZE_i)) \end{aligned} \tag{9}$$

We use average marginal effects to evaluate the direction and significance of how each independent variable affect the decision to invest. A significantly positive marginal effect means that the an increase in the value of the independent variable will increase the probability of postponing, a negative marginal effect means a higher value of the variable wil lead to proceeding. The marginal effect of the

| | |
|---|---|
| $DV_{i,t}^{postponing}$ | is the binary dependent variable which is one if a firm postponed generator $i$ in year $t$, and zero if the investment proceeded |
| $REGUNCERT_{s,t}$ | is an indicator variable which is one if there was regulatory uncertainty in state $s$ for year $t$, and zero otherwise |
| $T10_{t-1}$ | is the ten-year U.S. Treasury note interest rate in year $t-1$ |
| $PCAP_{s,t-1}$ | is the relative planned capacity in state $s$, in year $t-1$ |
| $RM_{k,t-1}^{pred(+1y)}$ | is the year $t-1$ prediction of reserve margin in region $k$ in year $t$ |
| $RHH_{is,t-1}$ | is the spark spread for generator $i$ in state $s$, in year $t-1$ |
| $TG_{i,t}$ | is the total number of existing generators owned by the owner of generator $i$, in year $t$ |
| $SIZE_i$ | is the summer capacity of generator $i$ |
| $F(\cdot)$ | is the logistic cumulative density function |

binary variable REGUNCERT can precisely be interpreted as the change in probability of a generator being canceled or postponed when the independent variable changes from 0 to 1. The marginal effect of continuous variables is explained in more detail in Appendix B.1. In order to identify and rank the most important variables in our regressions we use the Wald test to check the significance of each variable in the individual and multivariate regression. McFadden Pseudo-$R^2$ and the log pseudolikelihood for each regression is included in the result tables for the interested reader.[26]

From Table 7 we see that the regulatory uncertainty variable is significant at the 1 % level with a positive marginal effect of 0.089 and 0.058 for the individual and multivariate regressions respectively. In other words, firms are 8.9 % more likely to postpone planned generators under regulatory uncertainty for the individual regression and 5.8 % more likely according to the multivariate regression. We put the most trust in the results from the multivariate regression as it considers other explanatory variables in combination with regulatory uncertainty. By solely analysing the individual regressions we risk misinterpreting to what degree the individual variable is responsible for the investment behavior as we ignore other factors that could have an even stronger effect. A positive marginal effect for regulatory uncertainty is in line with Fleten et al. (2012)'s finding that reactivation of previously shut down plants are more unlikely under regulatory uncertainty, Ishii and Yan (2011)'s findings that increased regulatory uncertainty leads to postponing of investments in generation capacity and Billingsley and Ullrich (2012)'s results that regulatory uncertainty has a depressive effect on investment. It also fits well with the real option theory from among others Majd and Pindyck (1987).

[26] McFadden Pseudo-$R^2$ is referred to as McFadden P-$R^2$ and log pseudolikelihood is referred to as Log P-L in the result tables

*Table 7: 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 multivariate regression. The average marginal effects for $REGUNCERT_{s,t}$ is measured for the discrete change from zero to one. ***, ** and * describes 1%, 5% and 10% significance level respectively.*

| | | | | | | | | Postponing |
|---|---|---|---|---|---|---|---|---|
| REGUNCERT | 0.089*** | | | | | | | 0.058 *** |
| T10 | | 0.085*** | | | | | | 0.092 *** |
| PCAP | | | -0.225*** | | | | | -0.278 *** |
| RM | | | | 0.436*** | | | | 0.366 *** |
| RHH | | | | | 0.004 | | | -0.008 *** |
| TG | | | | | | -0.005*** | | -0.006 *** |
| SIZE | | | | | | | 0.001*** | 0.001 *** |
| | | | | | | | | Statistics |
| McFadden P-$R^2$ | 0.42 % | 2.60 % | 0.91 % | 0.25 % | 0.03 % | 0.93 % | 1.30 % | 7.61 % |
| Log P-L | -5 791 | -5 665 | -5 762 | -5 801 | -5 813 | -5 761 | -5 740 | -5 373 |

All the macro variables are significant at the 1 % level for both the individual and multivariate regressions. The relative planned capacity has a negative effect as anticipated. A rush of new investment plans should indicate a positive investment climate, thus it seems natural that there should be relatively larger growth in the decision to proceed compared to postpone. The positive effect of the interest rate variable indicates that higher interest rates discourage early exercise of the option to invest. It appears reasonable that a high cost of capital would slow down the investment pace. Referring to the discussion about stationarity in Section 3.8, these effects could also possibly be time effects, and simply indicate that there were fewer investments in the early years. Reserve margin also has a positive effect; generator owners in states with high values of predicted reserve margins are more likely to postpone investments. Since a high reserve margin implies low profitability, this is as expected.

Companies that own many generators postpone less and the effect is significant at the 1 % level. Large companies may be more robust to make long term decisions and be less dependent on short term variations. Another factor is that the large companies in our sample are more likely to be utilities and state power companies that may not have to take the same profitability considerations as the other companies in our sample due to a guaranteed fair rate of return. These companies will to a large extent base their investment decisions on the future capacity needs in their areas of service. These considerations would most likely not be as volatile as some of the variations that could affect profitability calculations, such as electricity and gas prices.

The variable for generator size is significant at the 1 % level, with large generators being postponed more than smaller generators. Even though we had an ambiguous expectation to this variable as we make no assumptions to the level of future uncertainty, there might be a straight forward explanation for the observed effects. As a larger generator on average will have longer lead time and be less flexible, uncertainty will have a greater influence on the value. With a short lead time technology there will be less of a difference between the conditions at the point of making an investment decision and the point of the generator being operational, as compared with a long lead time technology. The value of the finished project is because of this more uncertain. We also have to consider that some of our observations of large generators being postponed may not actually be genuine postponings. As we use standard lead times from EIA (2009), it may be the case that some of the larger generators actually have longer lead times.

The spark spread approximation is not significant in the individual regression, but has the expected negative effect and is significant at 1 % in the multivariate regression. Looking at the multinomial regression of Section 4.3 we see that the variable is significant at the 1 % level for both the individual and multivariate regressions, but with a positive marginal effect. We do not have a good explanation for the seemingly spurious results of this variable. It might be that it does not capture the effects we intended in a satisfactory way. Creating a more robust measure of generator or firm level profitability or predicted future profitability would most likely be a significant improvement for our model. An initial improvement of this variable is introduced in the spark spread regression model in Section 5 where we use daily wholesale electricity prices instead of annual retail electricity prices.

## 4.2 Decisions to Cancel: Full Sample Regression

In this section we study how the different variables affect a firm's decision to cancel a planned investment. We have a total of 5,487 relevant generator-year observations, of which 1,483 generators were canceled and 4,004 generators proceeded with the investment. Multicollinearity is not an issue in the full sample cancel regression as the correlation between the independent variables is low. Goodness of fit for the cancel model is assessed using a Hosmer-Lemeshow test. We do not get a good fit for the cancel model. The test primarily measures the predictive power of the model. High predictive power is not the primary goal of this study; the focus is rather testing the effects of the various chosen variables on investment behavior. With our large dataset, only seven explanatory variables, no interaction variables and lumpy occurrence of events it is natural that the Hosmer-Lemeshow test yield such results. The receiver operating curve for the cancel regression tells us that the model is more likely to correctly predict investment behavior than a random model. All these statistic test results and other statistics are discussed in detail in Appendix B. The individual and multivariate logistic regressions are presented in Table 8.

### 4.2.1 Individual and Multivariate Regressions

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

$$\begin{aligned} DV_{i,t}^{cancel} &= F(\beta_0 + (\beta_1 \times REGUNCERT_{s,t}) + (\beta_2 \times T10_{t-1}) \\ &+(\beta_3 \times PCAP_{s,t-1}) + (\beta_4 \times RM_{k,t-1}^{pred(+1y)}) + (\beta_5 \times RHH_{is,t-1}) \\ &+(\beta_6 \times TG_{i,t}) + (\beta_7 \times SIZE_i)) \end{aligned} \tag{10}$$

| | |
|---|---|
| $DV_{i,t}^{cancel}$ | 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 4.1. |

As in the postponing regression, the regulatory uncertainty variable is significant at the 1 % level with a positive marginal effect for both for the individual and multivariate regressions, as shown in Table 8. However, when referring to the available literature the results may be more surprising as many authors find that increased uncertainty increases the value of the option to invest, hence this should not induce agents to cancel investment, see Section 1. Tesiberg (1993) describes how asymmetric uncertainty in regulated industries may make canceling the optimal decision under regulatory uncertainty. Most of the theoretic literature, e.g. Majd and Pindyck (1987) and Brennan and Schwartz (1985), uses unregulated models that assumes symmetrical uncertainty. However in a regulated or partially regulated industry like the electric generation industry, regulatory profit restrictions may create asymmetric uncertainty and hence asymmetric risks. These restrictions exist in different forms, and will create an asymmetry unless there are similar loss restrictions.

Tesiberg (1993) reports how utilities reduced investment as they perceived a change in the regulatory environment with regards to expenditure allowance. Even though we have no indication that this is the case in our observation period, we believe that there may exist a similar uncertainty asymmetry in the case of deregulation. Due to price caps, rate freezes and other limitations, a company that is already making a fair rate of return on investments with little downside, might find itself in a situation with a full downside, but not a full upside. This possible phenomenon is related to the missing money problem described in Section 1.

As previously mentioned, Ishii and Yan (2011) assumes that restructuring was considered inevitable before year 2000. If companies had this expectation, then the uncertainty would be related to timing and the form of the deregulation. From past experiences with deregulations, there would most likely be a subset of alternative outcomes. If a firm considers all of these alternatives disadvantageous, and considers this to be the full set of outcomes, there will effectively be no uncertainty. The company will believe that it is inevitable that the process ends with a negative result, and hence canceling could seem like the optimal choice. This could happen in parallel to other investors experiencing uncertainty regarding the outcome due to different objectives, or because the assumption of inevitable restructuring is not shared.

Postponing generator investment is the equivalent of keeping an option to build a generator later. As there can be costs associated with postponing, this option may not be free. It is necessary that the option value is greater than the option price for postponing to be optimal in the face of uncertainty. There will naturally also be costs associated with canceling. Potential site cleanup would most likely be the main cost, but there can also be partial reversibility, meaning that the company could for instance sell some of the installed machinery and collect a salvage value. For canceling to be optimal when there is uncertainty, the net cost of canceling would have to be less than the expected cost of postponing, given that the cost of postponing is larger than the option value and the cost of canceling is negative. Because of this it may sometimes be optimal to cancel an investment when uncertainty increases.

*Table 8: 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 multivariate model. The average marginal effects for $REGUNCERT_{s,t}$ is measured for the discrete change from zero to one. ***, ** and * describes 1%, 5% and 10% significance level respectively.*

| | | | | | | | | Cancel |
|---|---|---|---|---|---|---|---|---|
| REGUNCERT | 0.088*** | | | | | | | 0.056 *** |
| T10 | | 0.062*** | | | | | | 0.069 *** |
| PCAP | | | 0.158*** | | | | | 0.063 *** |
| RM | | | | -0.191* | | | | 0.293 *** |
| RHH | | | | | -0.039*** | | | -0.046 *** |
| TG | | | | | | -0.007*** | | -0.007 *** |
| SIZE | | | | | | | 0.001*** | 0.001 *** |
| | | | | | | | | Statistics |
| McFadden P-$R^2$ | 0.57 % | 1.73 % | 1.07 % | 0.07 % | 3.75 % | 1.38 % | 0.45 % | 9.27 % |
| Log P-L | -3 183 | -3 146 | -3 167 | -3 199 | -3 082 | -3 157 | -3 188 | -2 905 |

We believe that the common theoretical view of uncertainty might sometimes not capture all necessary real world aspects in practice. As we mention in the previous paragraph there can sometimes exist asymmetric uncertainty. We also believe that regulatory uncertainty can have different effects for different companies. An IPP would clearly view regulatory uncertainty in a regulated state as something positive, there will be a possibility of going from not being allowed market access to being able to enter the market and compete. A utility might view this in a different fashion, even when disregarding the aforementioned asymmetry. Larsen and Bunn (1999) mentions the unprecedented strategic uncertainty previously regulated companies face as a consequence of deregulation. Companies that have previously been sheltered from competition may have to compete with firms that have long experience with competitive markets. Differences in cost position and financial strength may also contribute to different outlooks on regulatory uncertainty.

When moving from a regulated stable situation, to a state of regulatory uncertainty, the perceived chance of competition being implemented goes from close to zero to a significant level. If the company in question regards its own ability to compete as inferior, this means that the probability of a negative outcome has increased and because of this, investment might not appear as beneficial as originally intended. This may make the company inclined to cancel the investment as it possibly will want to make itself more flexible or invest in other parts of the organization. The thinking of the organization may have to change as a result of the possible future strategic uncertainty and the organization would possibly prefer a proactive stance rather than waiting. Also, companies that are actively tracking the deregulation process may perceive uncertainty to a lesser degree than we assume. By being involved in the process they could be confident about the outcome before the formal decision has been made, and because of this it is possible that some of our observed cancelings under regulatory uncertainty actually happened as the generator owner concluded about the uncertainty outcome.

The marginal effect of relative planned capacity is positive and significant at 1 % for both the individual and multivariate regression. A high level of planned capacity in a state increases the probability of canceling investments, this seems reasonable as very high levels of planned capacity could indicate an excessive investment level and thus lower future profitability. As in the case of the postponing regression, the interest rate variable has a positive effect that is significant at the 1 % level for both regressions. Higher interest rates makes investments less profitable and it seems natural that this could cause more canceling of no longer profitable investments.

In the case of reserve margin, the variable has a negative effect significant at the 10 % level for the individual regression and a positive effect significant at the 1 % level when the other variables are included. Looking at the multinomial regression in section 4.3 the variable still does not yield consistent results. The increased adoption of demand response mechanisms[27] and the expectations for future demand response mechanism in the later years, may help explain our spurious reserve margin results. NYISO, PJM, MISO, ISO-NE and several other regional transmission organizations have demand response programs (Cappers et al., 2010). Increased demand response resources will reduce prices in periods of scarcity[28] and utilities' expectations for this development can therefore influence their behavior for a given level of reserve margin. As advances in real time price signaling is made possible by technological development, Walawalkar et al. (2010) describes an expectation for increased demand response participation in the future. This may influence current investment decisions without being captured by our model, and a given reserve margin may be viewed inconsistently by generator owners at different times in our observation period. The missing money problem from section 1, could also yield a similar effect. For varying severities of the missing money problem, there will exist different equilibrium reserve margins that will give a sufficient number of days with high prices to recover capital costs. This could also lead to the event that a certain level of reserve margin has dissimilar effects at different times.

The spark spread approximation variable is significant at the 1 % level and as expected higher values decreases the probability of canceling. The variable indicates profitability and it appears intuitive that reduced profitability should lead to more canceling of investments.

Canceling occurs less for companies that own many generators. This is as anticipated, and several explanations can be offered. The diversification and financial flexibility that large companies are more likely to experience is one such explanation (Moel and Tufano, 2002). The fact that the early 2000s collapse of the merchant market was primarily an IPP driven bubble is another. And, as mentioned in section 4.1.1, larger companies in our sample are more likely to be companies that have some form of loss restriction.

Larger generators are canceled more than small generators and the variable is significant at the 1 % level for both regressions. We expected an ambiguous effect, the

[27]Demand response defined by Cappers et al. (2010) "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized."

[28]Electricity traditionally has almost perfectly inelastic short term price elasticity of demand, primarily because of customers not being able to observe instantaneous prices. Demand response mechanisms make demand more elastic, and because of reduction in demand in periods of scarcity, prices in these periods will be reduced. Demand resource resources are treated like capacity in many markets and because of this you could also view the aforementioned reduction of demand as an increase in supply.

positive effect can possibly be explained by the general shift in industry preference towards smaller, less capital intensive technologies described by Tesiberg (1994).

### 4.3 Multinomial Logistic Regression

$$
\begin{aligned}
DV_{i,t}^{multi} = F(\beta_0 + (\beta_1 \times REGUNCERT_{s,t}) + (\beta_2 \times T10_{t-1}) \\
+(\beta_3 \times PCAP_{s,t-1}) + (\beta_4 \times RM_{k,t-1}^{pred(+1y)}) + (\beta_5 \times RHH_{is,t-1}) \\
+(\beta_6 \times TG_{i,t}) + (\beta_7 \times SIZE_i))
\end{aligned}
\tag{11}
$$

| | |
|---|---|
| $DV_{i,t}^{multi}$ | 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 4.1 |

The multinomial regression allows simultaneous modeling of all three choices, proceeding, postponing and canceling. The results for the most part matches the results obtained in the regressions of section 4.1.1 and 4.2.1. The main difference stems from the variables that displayed unexpected behavior. For canceling, reserve margin is not significant in the full regression. The change of sign between the individual and multivariate regression is the same as in the previous regression. For postponing, the spark spread approximation is significant at 1 % with high values of the variable indicating an increased probability for postponing. This is the opposite of what we expected and different from the negative effect in the multivariate regression of section 4.1.1 and the insignificant result from the individual regression in the same section. Also regulatory uncertainty is significant at the 5 % level for postponing in the multinomial regression compared with 1 % in section 4.1.1. Generator size is not significant in the individual regression for canceling. We expected an ambiguous effect from this variable, so it is not surprising. As the results from this model are to a large extent in line with the significant results from section 4.1.1 and 4.2.1, it strengthens our belief in the validity of the observed effects.

*Table 9: 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 multinomial regression. ***, ** and * describes 1%, 5% and 10% significance level respectively.*

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Postponing | |
| REGUNCERT | 0.012*** | | | | | | | 0.032 | ** |
| T10 | | 0.069*** | | | | | | 0.069 | *** |
| PCAP | | | -0.291*** | | | | | -0.324 | *** |
| RM | | | | 0.491*** | | | | 0.237 | *** |
| RHH | | | | | 0.018*** | | | 0.009 | *** |
| TG | | | | | | -0.003*** | | -0.004 | *** |
| SIZE | | | | | | | 0,001*** | 0.001 | *** |
| | | | | | | | | Cancel | |
| REGUNCERT | 0.031*** | | | | | | | 0.027 | *** |
| T10 | | 0.012*** | | | | | | 0.020 | *** |
| PCAP | | | 0.160*** | | | | | 0.122 | *** |
| RM | | | | -0.244*** | | | | 0.082 | |
| RHH | | | | | -0.028*** | | | -0.030 | *** |
| TG | | | | | | -0.002*** | | -0.003 | *** |
| SIZE | | | | | | | 0,001 | 0.000 | *** |
| | | | | | | | | Statistics | |
| McFadden Pseudo-$R^2$ | 0.31 % | 1.63 % | 1.43 % | 0.24 % | 1.67 % | 0.73 % | 0.76 % | 7.24 % | |
| Log pseudolikelihood | -9 963 | -9 832 | -9 851 | -9 970 | -9 827 | -9 922 | -9 918 | -9 271 | |

# 5 Spark Spread Sample Regression

In this section we use a similar model to the one used in Sections 4.1, 4.2 and 4.3 for the years 2003 to 2011. We do this for two reasons, the first is to validate the results from these sections on a subsample. The second is to test our profitability uncertainty variable, the spark spread standard deviation, for the individual generators. We were not able to calculate this in the full sample regressions, because of lacking daily wholesale electricity price data from years before 2001. Figure 4 illustrates the occurrences of the three investment decisions used in the spark spread regression analysis for each year.

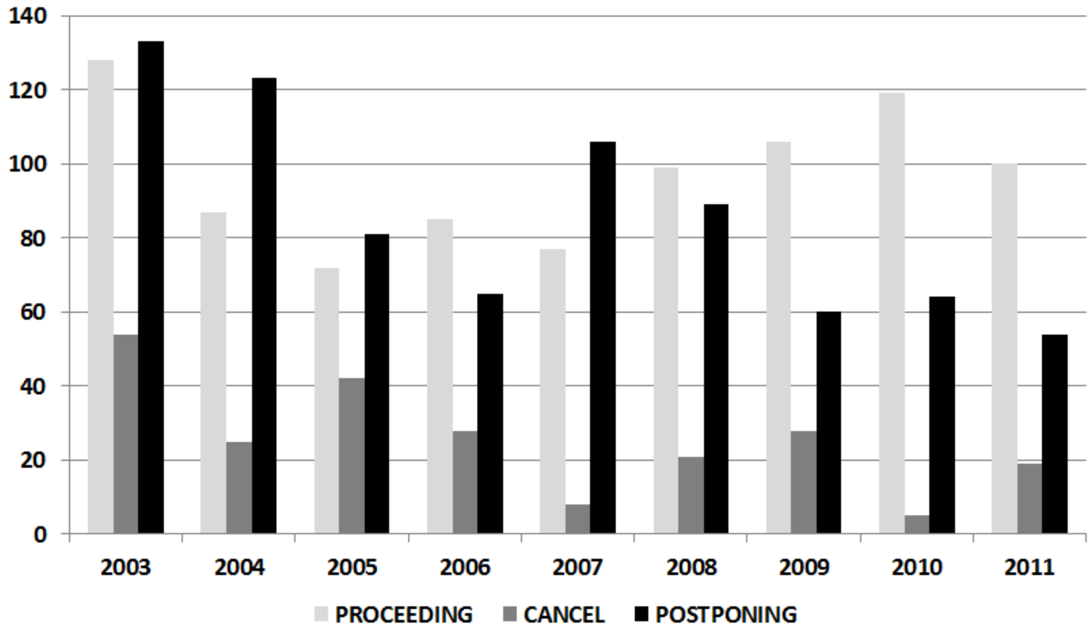



*Figure 4: Occurrences of the three different investment decisions used in the spark spread regression analysis by year from 2003 to 2011.*

The years 2003 to 2011 are chosen so that the collapse of the merchant market is not included in the sample. Because of this we do not include the variable for relative planned capacity, as it was designed to control for this trend. We do not have daily wholesale electricity price data for all U.S. states during the time frame from 2003 to 2010, some states are therefore omitted in the spark spread sample regression.[29] The U.S. states included belong to regions where sufficient price data

[29]The states omitted are: Florida, Kansas, Nebraska, Oklahoma, New Mexico and Arkansas (All associated with the Southwest Power Pool). States associated with the Midcontinent Independent System Operator (MISO) are included from 2006 to 2010 due to lack of price data.

exists in order to construct the spark spread standard deviation variable. These regions are listed in Table 5 in Section 3.6. The only other change from the full sample regression is the use of daily wholesale electricity price data to calculate the spark spread variable that replaces the spark spread approximation variable (RHH). The use of wholesale prices should make the variable more precise as these are the prices generator companies obtain in the market. For completeness, we still comment on the results obtained by keeping the spark spread approximation variable.

## 5.1 Decisions to Postpone: Spark Spread Sample Regression

Here we investigate the factors that affect a firm's decision to postpone a planned investment. For the spark spread sample regression we have a total of 1,648 relevant generator-year observations, of which 775 generators were postponed and 873 generators proceeded with the investment. The individual and multivariate regressions are presented in Table 10.

### 5.1.1 Individual and Multivariate Regressions

The multivariate logistic regression used in order to analyse the spark spread sample is explained in Equation (12). The results from the regressions are presented in Table 10. We get a positive effect for the regulatory uncertainty variable, significant at 1 % level in both the individual and multivariate regression. We see a large increase in the marginal effect of the REGUNCERT variable from 5.8 % in the full sample regression to 23.9 % in the spark spread sample regression. This means that the probability of postponing investments is 23.9 % higher when generators are situated in states that change from no regulatory uncertainty to regulatory uncertainty. The high increase in probability could be a result of the few regulatory uncertainty observations in the spark spread sample as only four states experience regulatory uncertainty from 2003 to 2012. The low number of observations makes the results less trustworthy, as random effects are more likely to appear. Taking this into account, the direction and significance of the marginal effect is the same as in the full sample regression, which is in line with real option theory as explained in Section 4.1. The spark spread standard deviation variable also has a positive marginal effect and is significant at 5 % for the individual regression and 1 % for the multivariate regression. This means that uncertainty regarding the operating profitability increase the probability of postponing.

$$DV_{i,t}^{postponing} = F(\beta_0 + (\beta_1 \times REGUNCERT_{s,t}) + (\beta_2 \times SPRDSD_{ik,t-1}) + (\beta_3 \times RM_{k,t-1}^{pred(+1y)}) + (\beta_4 \times T10_{t-1}) + (\beta_5 \times \overline{SPRD}_{ik,t-1}) + (\beta_6 \times TG_{i,t}) + (\beta_7 \times SIZE_i)) \quad (12)$$

| | |
|---|---|
| $DV_{i,t}^{postponing}$ | is the binary dependent variable which is one if a firm postponed generator $i$ in year $t$, and zero if the investment proceeded |
| $REGUNCERT_{s,t}$ | is an indicator variable which is one if there was regulatory uncertainty in state $s$ for year $t$, and zero otherwise |
| $SPRDSD_{ik,t-1}$ | is the spark spread standard deviation for generator $i$ in region $k$, in year $t-1$ |
| $RM_{k,t-1}^{pred(+1y)}$ | is the year $t-1$ prediction of reserve margin in region $k$ in year $t$ |
| $T10_{t-1}$ | is the ten-year U.S. Treasury note interest rate in year $t-1$ |
| $\overline{SPRD}_{ik,t-1}$ | is the spark spread for generator $i$ in region $k$, in year $t-1$ |
| $TG_{i,t}$ | is the total number of existing generators owned by the owner of generator $i$, in year $t$ |
| $SIZE_i$ | is the summer capacity of generator $i$ |
| $F(\cdot)$ | is the logistic cumulative density function |

This effect is what is predicted by real option theory as higher uncertainty raises the early exercise boundary of the call option to invest. We expected a more ambiguous effect because of the nature of the generators we are studying. Most intermediate and peak load plants are only dispatched when electricity prices reaches levels that make them profitable to operate. Owners of such power plants have the ability to ramp up and down electricity production whenever production is profitable. A higher profitability uncertainty could thus create a substantial upside with low potential downside for the investor as the investor can shut down production once prices gets too low. The call option effect and the ability to ramp up and down production affect investor behavior in different directions, which is what led us to believe we would see an inconclusive effect of this variable on the decision to postpone in the first place. These two effects of spark spread standard deviation are discussed in more detail in Section 3.6. Our results lend support to the call option effect being the stronger of the two in the full sample regression. It would be natural to expect a different degree of significance and direction of the marginal effect of the spark spread standard deviation variable for intermediate versus peak load plants, as was discussed in Section 3.6. We have done a rough estimate of this difference by defining peak load plants as combustion turbines with summer capacity below 200 MW and combined cycle turbines with summer capacity below 100 MW, the remaining plants are defined as intermediate load plants. According to EIA (2009), a conventional combustion turbine has an average capacity of 160 MW while a conventional combined cycle combustion turbine has an average capacity of 250 MW. Most combustion turbines operate at peak load while the more efficient combined cycle plants mostly operate at intermediate load. We therefore believe that the thresholds we have chosen give a fair estimate of which plants function as peak and intermediate load in our data. When we run the spark spread sample regression on the generators defined as peak load plants we get negative sign of the marginal effect and no significance for the spark spread standard deviation variable in the multivariate regression. When we run the spark spread sample regression on the intermediate load plants we get a positive marginal effect at the 1 % significance level in the multivariate regression. This means that intermediate load plants are more likely to postpone an investment during profitability uncertainty while peak load plants have a more ambiguous response to higher profitability uncertainty. These results are in line with the real option theory presented in Section 3.6 as we get a stronger call option effect for the intermediate load plants relative to the peak load plants. Peak load plants are more affected by the flexibility effect, i.e. they are less likely to postpone investments during times of high profitability uncertainty as there could be considerable profit opportunities for peak load plants in such price environments.

*Table 10: 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 multivariate regression. The average marginal effects for $REGUNCERT_{s,t}$ is measured for the discrete change from zero to one. ***, ** and * describes 1%, 5% and 10% significance level respectively.*

| | | | | | | | | Postponing |
|---|---|---|---|---|---|---|---|---|
| REGUNCERT | 0.274*** | | | | | | | 0.239 *** |
| SPRDSD | | 0.005** | | | | | | 0.007 *** |
| RM | | | 0.189 | | | | | 0.227 |
| T10 | | | | 0.491*** | | | | 0.044 |
| SPRD | | | | | -0.000 | | | -0.018 *** |
| TG | | | | | | -0.005*** | | -0.045 *** |
| SIZE | | | | | | | 0.001*** | 0.004 *** |
| | | | | | | | | Statistics |
| McFadden P-$R^2$ | 0.70 % | 0.36 % | 0.05 % | 1.30 % | 0.44 % | 2.80 % | 3.30 % | 8.69 % |
| Log P-L | -1 131 | -1 135 | -1 139 | -1 124 | -1 126 | -1 108 | -1 101 | -1 040 |

Spark spread has a negative marginal effect that is insignificant for the individual regression and significant at 1 % for the multivariate regression. These results are equivalent to the results we got for the spark spread approximation variable in the full sample regression in Section 4. High spark spread indicates high profitability and it appears natural that improved profitability should lead to earlier exercise of the option to invest as the cost of deferring operation increases. Using the spark spread approximation variable in the multivariate spark spread sample regression we get a negative effect significant at 5 %. The reduced significance could indicate that using wholesale prices more strongly captures the intended profitability effects. Still, it is worth mentioning that we get the expected effects using the spark spread approximation variable in both the full and spark spread sample regressions. This indicates that using retail prices when calculating spark spread could be a satisfactory approximation for generator profitability, at least in this sample.

The interest rate and reserve margin variables do not give the same results as in Section 4.1. Interest rate is significant at 1 % in the individual regression, but is not significant in the full regression. By including only the years after 2003 our sample contains relatively few years, and includes several years of very low interest rates following the financial crisis of 2007-2008, see Figure 7. This gives a limited observation range for the variable. Also, it is worth noting that we can obtain similar results in the canceling regression in Section 5.2.1, with highly significant effects in the individual regression and no significance in the full regression. This might indicate that the variable has significant positive effects as expected, and that these are captured by the other variables in the model for this sample. Reserve margin is not significant in the individual nor in the multivariate regression. The effects mentioned in Section 4.2.1, including demand response mechanisms and the missing money problem, are effects that would be an issue for all the years in the spark spread sample. Interpreting the variable may be difficult because of this. Generator size and the number of generators owned variables yield the same results as in the full sample regression.

## 5.2 Decisions to Cancel: Spark Spread Sample Regression

In this section we study how the different variables affect a firm's decision to cancel a planned investment. We have a total of 1,103 relevant generator-year observations, of which 230 generators were canceled and 873 generators proceeded with the investment. The individual and multivariate logistic regressions are presented in Table 11.

### 5.2.1 Individual and Multivariate Regressions

We use the following logistic regression in our analysis of the decision to cancel in the spark spread sample:

$$
\begin{aligned}
DV_{i,t}^{canceling} = F(\beta_0 + (\beta_1 \times REGUNCERT_{s,t}) + (\beta_2 \times SPRDSD_{ik,t-1}) + \\
(\beta_3 \times RM_{k,t-1}^{pred(+1y)}) + (\beta_4 \times T10_{t-1}) + (\beta_5 \times SPRD_{ik,t-1}) \\
+(\beta_6 \times TG_{i,t}) + (\beta_7 \times SIZE_i))
\end{aligned}
\tag{13}
$$

| | |
|---|---|
| $DV_{i,t}^{canceling}$ | 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 5.1.1. |

We find a significant positive influence for regulatory uncertainty, matching the results from the full sample regression. This is the opposite effect of what we expected, reasons and explanations for this effect are discussed in Section 4.2. For spark spread standard deviation we get positive effects, significant at the 5 % level for the individual regression and 1 % for the multivariate regression. This is not the results we expected as higher profitability uncertainty should be beneficial for power plants with the ability to ramp up and down production.

This should lead investors to go ahead and proceed with investments rather than cancel as higher uncertainty increases the probability of the spark spread reaching the levels needed in order for the power plants to be profitable. One possible explanation could be that the variable is not forward looking. When evaluating an investment it is future spark spread standard deviation that will determine how profitability is viewed. The current level may not reveal how investors forecast future values. A generator investment is long term with a life expectancy of > 25 years. If spark spread standard deviation is considered short term variation, it might not affect long term decision making. High short term variability may also point to future lower uncertainty levels if investors consider spark spread standard deviation to be mean reverting.

Variation may not give sufficient information, without accounting for the level. Even though a higher spark spread standard deviation should increase the probability of higher prices, it does not necessarily tell a potential investor what he needs to know without looking at the current profitability level at the same time. A generator that ramps up and down production depending on the spark spread, will have a certain boundary where production becomes profitable. The profitability of the generator will be determined by the number of hours the generator operates multiplied by the average spark spread obtained. Hence variations in the spark spread below the threshold will not affect profitability. Variations in spark spread above the threshold will give the same profitability as an identical average spark spread with less variance. We do not have a satisfactory explanation for the spark spread standard deviation results, there may be an identification problem related to the mentioned factors, which causes the variable not to measure all the desired profitability uncertainty effects. For a given planned generator, it could seem reasonable that other factors may have to be included to capture the outlook to future utilization and profitability.

*Table 11: 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 multivariate model. The average marginal effects for $REGUNCERT_{s,t}$ is measured for the discrete change from zero to one. ***, ** and * describes 1%, 5% and 10% significance level respectively.*

| | | | | | | | | Cancel |
|---|---|---|---|---|---|---|---|---|
| REGUNCERT | 0.299*** | | | | | | | 0.256 *** |
| SPRDSD | | 0.004** | | | | | | 0.005 *** |
| RM | | | -0.349* | | | | | -0.141 |
| T10 | | | | 0.079*** | | | | 0.052 ** |
| SPRD | | | | | -0.002** | | | -0.003*** |
| TG | | | | | | -0.004*** | | -0.004*** |
| SIZE | | | | | | | 0.001*** | 0.001 *** |
| | | | | | | | | Statistics |
| McFadden Po-$R^2$ | 1.06 % | 0.45 % | 0.40 % | 1.08 % | 1.93 % | 0.92 % | 3.63 % | 9.71% |
| Log P-L | -558 | -562 | -562 | -558 | -550 | -559 | -544 | -510 |

We use the definition of peak and intermediate load plants that was presented and used in Section 5.1.1 in order to investigate the effect of spark spread standard deviation on the decision to cancel for peak load plants versus intermediate load plants. In the multivariate regression, peak load plants get a positive marginal effect at the 10 % significance level while intermediate load plants get a positive marginal effect at the 1 % significance level. This means that both intermediate and peak load plants are more likely to cancel during high levels of profitability uncertainty. Still, the significance levels suggest that the effects are larger for the intermediate load plants. We expected the direction of the marginal effect to be negative for both the intermediate and the peak load plants as higher profitability uncertainty should make it more profitable for plants with the ability to ramp up and down electricity production to operate. The result that intermediate load plants are more likely to cancel during high profitability uncertainty than peak load plants is in line with the theory explained in Section 3.6 as higher profitability uncertainty should be more of an advantage for peak load plants compared to intermediate load plants.

The spark spread variable is significant at the 5 % level in the individual regression and 1 % in the multivariate regression, with a negative marginal effect, as expected.

Exchanging it with the spark spread approximation variable from section 4, yields the same results.

Reserve margin is insignificant in the full regression and has a negative effect significant at the 5 % level in the individual regression. The variable had spurious results in the previous regressions as well, so this is not surprising. Some possible explanations are described in Section 4.2. Interest rate has a positive marginal effect and is significant at 1 % in the individual regression, and 5 % in the multivariate regression. These are the same effects we saw in the full sample regression. Higher interest rates increase the chance of canceling in both the individual and the multivariate regression.

The generator size and number of generators owned variables are significant at the 1 % level for both the individual and the multivariate regressions. Like in Section 4.2, the marginal effects is negative for number of generators owned and positive for the size of the generators.

# 6 Summary of Regression Results

In this section we summarize the regression results, Table 12 gives an overview. Two data samples are used for analysing the proposed generator data, the full sample where we use all data available going back to 1990 and the spark spread sample where we use a subsample from 2003 to 2011 and analyse the effect of profitability uncertainty, excluding the collapse of the merchant market. The variables used to analyse the two data samples differ slightly due to the lack of available wholesale price data prior to 2001 and because we choose to exclude the planned capacity variable from the spark spread sample regression.[30] We run logistic regressions investigating the factors that affect investors' willingness to postpone, proceed and cancel proposed investments on both data samples.

*Table 12: Summary of the regression results from the various multivariate regressions on both data samples. The sign of the marginal effects are given in parenthesis. ***, ** and * describes 1 %, 5 % and 10 % significance level respectively. A plus sign indicates that higher value of the variable will result in a higher probability of postponing or cancelling the investment. A minus sing indicates that a higher value of the variable will result in a higher probability of proceeding with an investment. The significance level tells us to what degree this result can be trusted.*

| **Variable** | **Full Sample** | | | | **Spark Spread Sample** | | | |
|---|---|---|---|---|---|---|---|---|
| | *POSTPONING* | | *CANCEL* | | *POSTPONING* | | *CANCEL* | |
| REGUNCERT | (+) | *** | (+) | *** | (+) | *** | (+) | *** |
| SPRDSD | | | | | (+) | *** | (+) | *** |
| T10 | (+) | *** | (+) | *** | (+) | | (+) | ** |
| PCAP | (−) | *** | (+) | *** | | | | |
| RM | (+) | *** | (+) | *** | (+) | | (−) | |
| RHH | (−) | *** | (−) | *** | | | | |
| SPRD | | | | | (−) | *** | (−) | *** |
| TG | (−) | *** | (−) | *** | (−) | *** | (−) | *** |
| SIZE | (+) | *** | (+) | *** | (+) | *** | (+) | *** |

We find that regulatory uncertainty increases the likelihood of proposed plants being postponed for all regressions. This result is in line with real option theory as increased uncertainty should delay investments as investors gather more information. A higher uncertainty regarding the profitability of each generator will also increase the probability of postponing. This is also consistent with option theory where increased uncertainty raises the early exercise boundary for the call option to invest. However, profitability uncertainty can affect the decision to postpone in two ways and should be different for peak load and intermediate load plants, as

[30] This is done as the planned capacity variable is created in order to control for the investment bubble prior to the merchant market collapse, which is only only present in the full sample regression.

explained in Section 3.6. We find that the plants we define as intermediate load plants are more likely to postpone investments during times of high profitability uncertainty than the plants we define as peak load. This is natural as peak load plants have a higher incentive to proceed when profitability uncertainty is high.

The largest firms and the more profitable generators are more likely to proceed with investments. Also, larger generators are more likely to be postponed and cancelled than smaller generators. A high interest rate increases the probability of canceling and postponing investments and generators situated in regions with high reserve margins are more likely to postpone according to the full sample regression.

Some of our results are counterintuitive. Investors are more likely to cancel planned generators during times of high regulatory uncertainty. According to real option theory more uncertainty increases the value of the option to invest, hence the option should not be canceled. We expected a more ambiguous effect of regulatory uncertainty on the decision to cancel as, among other things, outlook to regulatory change differs because companies view their own ability to compete differently. A more in depth discussion of the reasons why regulatory uncertainty could give these effects are found in Section 4.2.1.

Owners are also more likely to cancel planned generators during times of high profitability uncertainty. A higher spark spread standard deviation should also increase the option value as both peak and intermediate load plants have the ability to ramp up and down production. Higher uncertainty should thus increase the option value to invest in such plants. We do not have satisfactory explanations for these results, there may be identification problems related to the spark spread standard deviation variable, as discussed in Section 5.2.1.

# 7 Conclusion

This paper provides an empirical study of the real options to postpone, cancel and proceed with sequential investment with time-to-build. We study variables that affect the investment behavior in the U.S. electricity generation industry for gas fired combined cycle and combustion generators. The dataset uses generator level data for proposed power plants in 48 U.S. states in the years 1991 to 2011. The main regression results are summarized in Table 12 in Section 6.

We find strong evidence of real option effects. Regulatory uncertainty increases the probability of planned generators being postponed. Profitability uncertainty, proxied by spark spread volatility, yields the same results with higher variability leading to more postponing. This is consistent with real option theory which states that uncertainty should have a depressive effect on the sequential investment (Majd and Pindyck, 1987). We also find that larger and more irreversible intermediate load generator investments are more likely to be postponed than smaller peak load plants. This also lend support to the results of Majd and Pindyck (1987) in that time-to-build should further increase the depressive effect of uncertainty.

Somewhat more surprising is our result that that generators are more likely to cancel during times with high profitability uncertainty and regulatory uncertainty, as higher uncertainty should increase the real option value. This contradicts most real option theory. For the regulatory uncertainty results, it could be explained by the cost of postponing, industry specific uncertainty asymmetry or strategic considerations, as we discuss in Section 4.2.1. We do not have a good explanation for the spark spread standard deviation results, but we believe that the variable may suffer from some identification issues.

What could these results mean for policy makers? Our results show that regulatory uncertainty have the potential to inhibit capacity growth as it increases the likelihood of canceling and delaying power plant investments rather than completing the generator projects. Regulators should have this in mind while considering regulatory change. An investigation process for evaluating changed legislation, could lead to reduced investments. This may not be beneficial for the local electricity market as supply reliability could be threatened. Keeping regulatory processes brief is one of the measures that could be advisable. There have been large state level variations in the time span of the deregulation processes.

Further work should be done to improve the model. A natural starting point is to attempt modifying variables in order to capture forward looking effects. The profitability variables spark spread and spark spread approximation should be replaced by a variable that can capture the expected future profitability of generator companies. One alternative could be looking at future/forward contracts to get future prices.

We have not included any interaction variables or other higher order variables in our model. Interactions could improve the explanatory power of the model. As we have a large volume of data, another option to increase the explanatory power would be to add more variables. Including financial data would be a positive contribution. Finding a better way to control for the trend of the collapse of the merchant market could also potentially improve the model.

Further work should also include an attempt at quantifying the costs of postponing and canceling in different stages of the investment process. With these numbers it could be easier to build an understanding of the decisions to cancel and postpone and how they relate to each other, especially in the face of regulatory uncertainty. The analysis of the result that regulatory uncertainty increases the probability of canceling would be greatly improved by this knowledge. It could also shed some light on the relationship between uncertainty and canceling. Most empirical papers use aggregate investments when measuring real option effects. From this it is possible to say whether investments increase or decrease. It can however be difficult to determine whether the reduction comes from postponing or canceling. We believe that these ambiguities related to canceling and uncertainty could be addressed in a satisfactory way by quantifying the aforementioned costs.

# 8 Acknowledgements

We would like to thank our supervisor Professor Stein-Erik Fleten at Norwegian University of Science and Technology for professional guidance and comments. We also wish to thank Assistant Professor Carl Ullrich at James Madison University. He has provided us with valuable insight on the American utility industry and has always been available when help was needed. We want to acknowledge the help from Postdoctoral Fellow Erik Haugom at Norwegian University of Science and Technology for helping us structuring our source code and for providing us with valuable input throughout the course of our work. We also wish to thank Professor Mette Langaas, Professor John Sølve Tyssedal and Associate Professor Øyvind Salvesen at Norwegian University of Science and Technology for providing us with professional statistics guidance.

# References

Agresti, A. (1996), *An Introduction to Categorical Data Analysis*, first edn, Wiley, John & Sons.

Bar-Ilan, A. and Strange, W. C. (1996), 'Investment lags', *American Economic Review* **86**(3), 610–22.

Bar-Ilan, A. and Strange, W. C. (1998), 'A model of sequential investment', *Journal of Economic Dynamics and Control* **22**(3), 437–463.

Bernanke, B. S. (1983), 'Irreversibility, uncertainty, and cyclical investment', *The Quarterly Journal of Economics* **98**(1), 85–106.

Billingsley, R. and Ullrich, C. (2012), 'Regulatory uncertainty, corporate expectation, and unintended consequences'. Available at SSRN: http://ssrn.com/abstract=1944217 or http://dx.doi.org/10.2139/ssrn.1944217.

Black, F. and Scholes, M. S. (1973), 'The pricing of options and corporate liabilities', *Journal of Political Economy* **81**(3), 637–54.

Borenstein, S. and Bushnell, J. (2000), 'Electricity restructuring: Deregulation or reregulation', *Energy Policy* **23**(2), 46 – 52.

Brennan, M. J. and Schwartz, E. S. (1985), 'Evaluating natural resource investments', *The Journal of Business* **58**(2), 135–157.

Bulan, L. T. (2005), 'Real options, irreversible investment and firm uncertainty: New evidence from U.S. firms', *Review of Financial Economics* **14**(3-4), 255–279.

Cappers, P., Goldman, C. and Kathan, D. (2010), 'Demand response in U.S. electricity markets: Empirical evidence', *Energy* **35**(4), 1526 – 1535.

Cohen, J., Cohen, P., West, S. and Aiken, L. (2002), *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*, third edn, Routledge.

Cramton, P. and Stoft, S. (2006), 'The convergence of market designs for adequate generating capacity with special attention to the CAISO's resource adequacy problem'.

Cukierman, A. (1980), 'The effects of uncertainty on investment under risk neutrality with endogenous information', *Journal of Political Economy* **88**(3), 462–475.

Delmas, M. and Tokat, Y. (2005), 'Deregulation, Governance Structures, and Efficiency: The U.S. Electric Utility Sector', *Strategic Management Journal* **26**(5), 441–460.

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

Duane, T. P. (2002), 'Regulation's rationale: Learning from the California energy crisis', *Yale Journal on Regulation* **19**(2), 471–540.

Dunne, T. and Mu, X. (2010), 'Investment spikes and uncertainty in the petroleum refining industry', *Journal of Industrial Economics* **58**(1), 190–213.

EIA (2000), The changing structure of the electric power industry 2000: An update, available at:, Technical report, EIA.

EIA (2009), Annual energy outlook, Technical report, EIA, http://www.eia.gov/oiaf/archive/aeo09/assumption/pdf/0554(2009).pdf.

EIA (2014*a*), 'Electricity day-ahead wholesale prices [online], available at:', *http://www.eia.gov/electricity/wholesale/* (Viewed 12 March 2014).

EIA (2014*b*), 'Status of electricity restructuring by state [online], available at:', *http://www.eia.gov/electricity/policies/restructuring/* (Viewed 10 May 2014).

Eikemo, T. and Clausen, T. (2007), *Kvantitativ analyse med SPSS*, first edn, Tapir Akademisk Forlag.

Fabrizio, K. (2013), 'The effect of regulatory uncertainty on investment:evidence from renewable energy generation', *The Journal of Law, Economics, and Organization* **29**(4), 765–798.

FERC (2014), 'National overview of electric power markets [online], available at:', *http://www.ferc.gov/market-oversight/mkt-electric/overview.asp* (Viewed 21 March 2014).

Finon, D. (2008), 'Investment risk allocation in decentralised electricity markets - the need of long-term contracts and vertical integration', *OPEC Energy Review* **32**, 150–183.

Fleten, S.-E., Haugom, E. and Ullrich, C. (2012), 'Keeping the lights on until the regulator makes up his mind'. Available at http://www.realoptions.org/openconf2013/data/papers/25.pdf.

Fraser, P. (2003), Power generation investment in electricity markets, Technical report, IEA, http://www.hks.harvard.edu/hepg/Papers/Fraser.gen.invest.elec.mkts.1203.pdf.

Ishii, J. and Yan, J. (2011), 'Investment under regulatory uncertainty: U.S. electricity generation investment 1996-2000'.

Joskow, P. (2006), 'Competitive electricity markets and investment in new generating capacity'. Available at SSRN: http://ssrn.com/abstract=902005 or http://dspace.mit.edu/handle/1721.1/45055.

Joskow, P. L. (2005), *Electricity Deregulation - Choices and Challenges*, University Of Chicago Press, chapter The difficult transition to competitive electricity markets in the U.S.

Kellogg, R. (2010), 'The effect of uncertainty on investment: Evidence from Texas oil drilling'.

Kutner, M., Nachtsheim, C. and Neter, J. (2004), *Applied Linear Regression Models*, fourth edn, McGraw-Hill.

Larsen, E. R. and Bunn, D. W. (1999), 'Deregulation in electricity: understanding strategic and regulatory risk', *The Journal of the Operational Research Society* **50**(4), 337–344.

Long, J. and Freese, J. (2006), *Regression Models for Categorical Dependent Variables Using Stata*, second edn, Stata Press.

Majd, S. and Pindyck, R. (1987), 'Time to build, option value, and investment decisions', *Journal of Financial Economics* **40**, 7–27.

McDonald, R. (2006), *Derivatives Markets*, Addison-Wesley Series in Finance, Addison Wesley.

McDonald, R. L. (2000), *Project Flexibility, Agency, and Competition*, Addison-Wesley, chapter Real options and rules of thumb in capital budgeting.

McDonald, S. and Siegel, D. (1986), 'The value of waiting to invest', *Quartely Journal of Economics* **101**, 707–728.

Merton, R. C. (1973), 'Theory of rational option pricing', *Bell Journal of Economics* **4**(1), 141–183.

Milne, A. and Whalley, E. (2000), 'Time to build, option value and investment decisions; a comment', *Journal of Financial Economics* **56**, 325–332.

Moel, A. and Tufano, P. (2002), 'When are real options exercised? An emirical study of mine closing', *Review of Financial Studies* **1**(15), 35–64.

Näsäkkäla, E. and Fleten, S.-E. (2005), 'Flexibility and technology choice in gas fired power plant investments', *Review of Financial Economics* **14**(2), 371 – 393.

Quigg, L. (1993), 'Empirical testing of real option-pricing models', *The Journal of Finance* **47**(2), 621–640.

Roberts, K. and Weitzman, M. L. (1981), 'Funding criteria for research, development, and exploration projects', *Econometrica* **49**(5), 1261–1288.

Rodilla, P. and Batlle, C. (2012), 'Security of electricity supply at the generation level: Problem analysis', *Energy Policy* **40**(0), 177 – 185.

Schubert, E., Hurlbut, D., Adib, P. and Oren, S. (2006), 'The Texas energy-only resource adequacy mechanism', *The Electricity Journal* **19**, 39–49.

Slade, M. E. (2013), 'Investment and uncertainty with time to build: Evidence from U.S. copper mining'. Available at http://www.economics.ubc.ca/files/2013/10/TimeToBuild1013.pdf.

Sødal, S. (2006), 'Entry and exit decsions based on a discount factor approach', *Journal of Economic Dynamics and Control* **30**(11), 1963–1986.

Tesiberg, E. (1993), 'Capital investment strategies under uncertain regulation', *The RAND Journal of Economics* **24**(4), 591–604.

Tesiberg, E. (1994), 'An option valuation analysis of investment choices by a regulated firm', *Management Science* **40**(4), 353–348.

Triantis, A. J. (2005), 'Realizing the potential of real options: Does theory meet practice', *Journal of Applied Corporate Finance* **17**(2), 8–16.

Trigeorgis, L. (1996), *Real Options : Managerial Flexibility and Strategy in Resource Allocation*, MIT Press.

Walawalkar, R., Fernands, S., Thakur, N. and Chevva, K. (2010), 'Evolution and current status of demand response (DR) in electricity markets: Insights from PJM', *Energy* **35**(4), 1553 – 1560.

Wangensteen, I. (2011), *Power System Economics - The Nordic Electricity Market*, Tapir Academic Press.

# A Data and Independent Variables

## A.1 Status Transition Figures

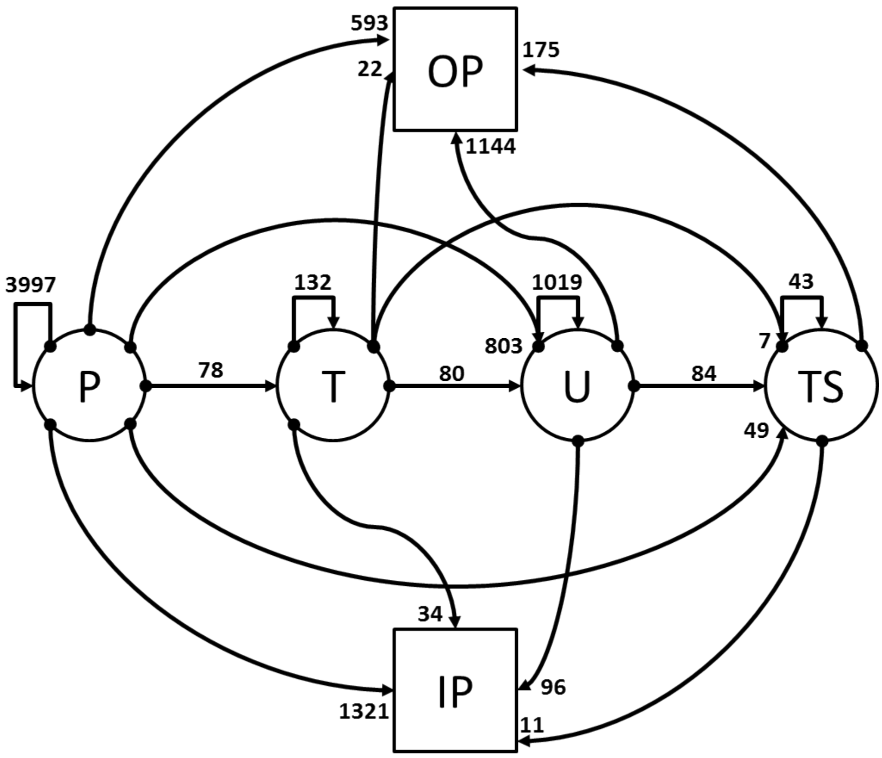



*Figure 5: The figure shows the number of observed transitions between the different investment stages in the full sample regression. The arrows indicate the direction of transitions. The number close to an arrow indicates the occurrence of this transition in the dataset. Investment stages are incorporated into circles and final stages are incorporated into squares. Definitions of status codes: P = Planned, no regulatory approval, T =Planned, Regulatory approval received, U = Under construction, TS = Construction complete, not in operation, OP = Operating, IP = Canceled.*

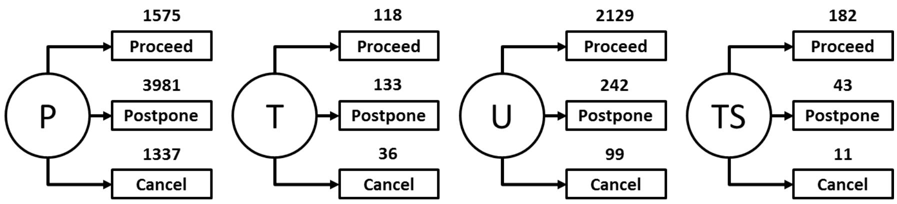



*Figure 6: The figure shows the number of transitions from each investment stage to the three statuses: proceed, postpone and cancel. By summing up the numbers we get a total of 4004, 4399 and 1483 observations of proceeding, postponing and canceling respectively. Investment stages are incorporated into circles and type of transition is incorporated into rectangles. Definitions of status codes: P = Planned, no regulatory approval, T =Planned, Regulatory approval received, U = Under construction, TS = Construction complete.*

## A.2 Macro Data

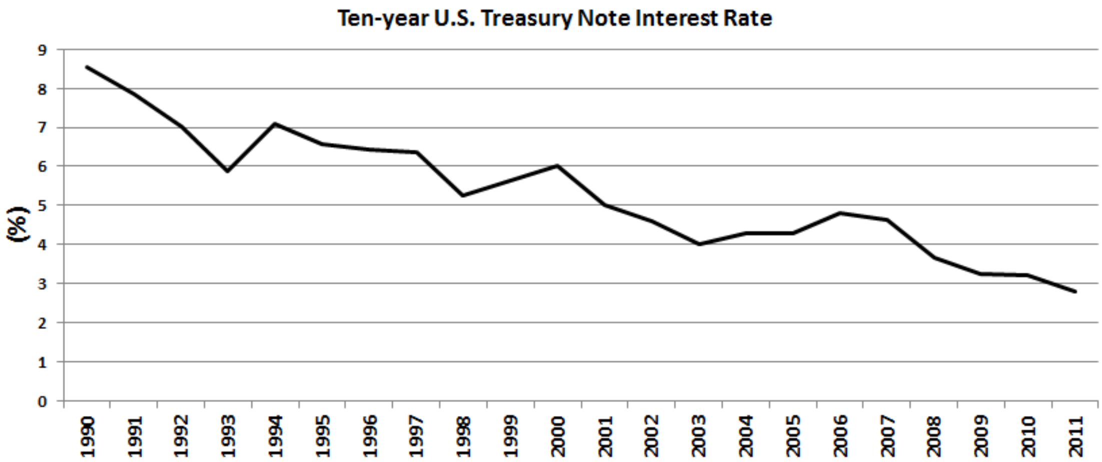



*Figure 7: The figure shows annual ten-year U.S. Treasury Interest Rate for the years relevant to our study. Price data gathered from FED.*

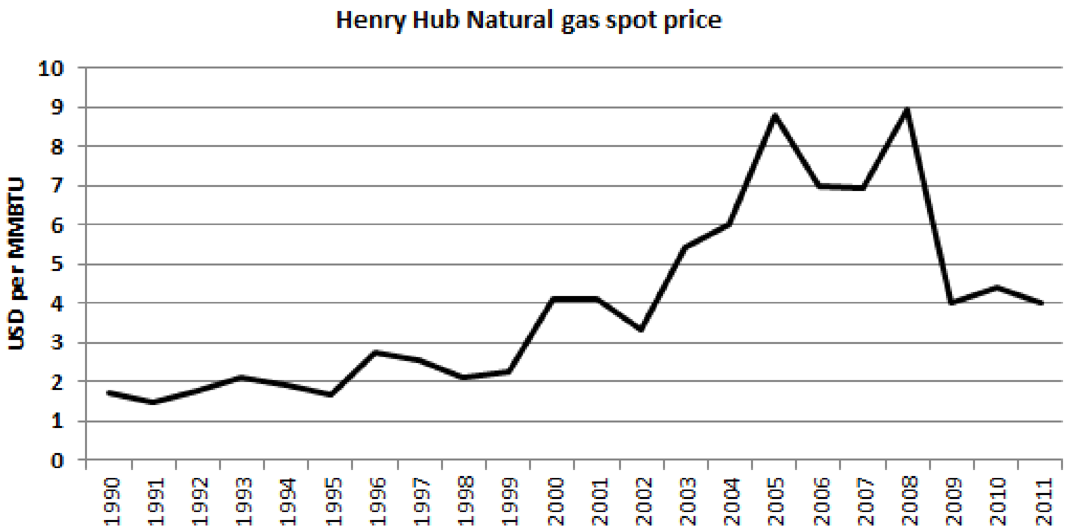



*Figure 8: Henry hub annual spot prices. Price data gathered from Reuters*

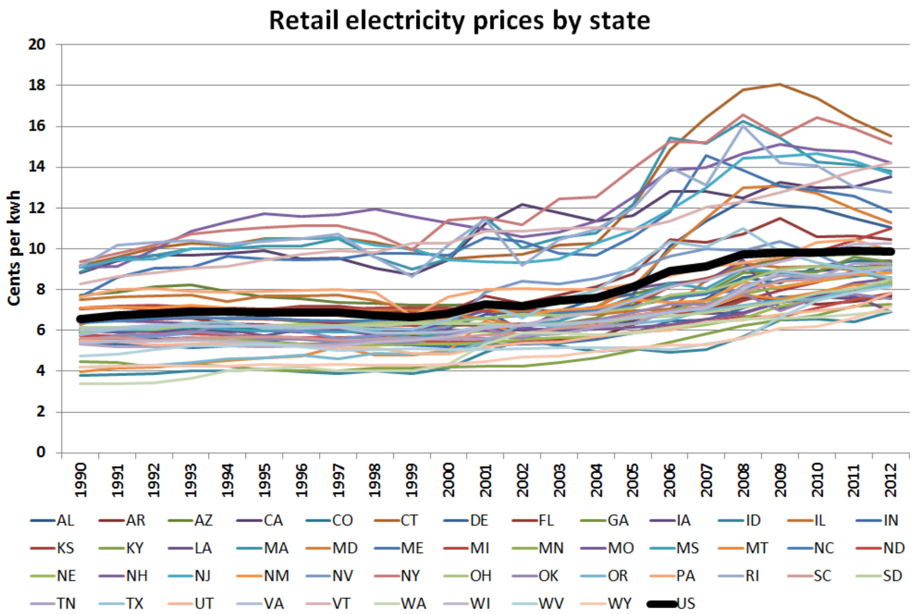



*Figure 9:* *The figure show the annual retail electricity prices for all U.S. states included in our study. The bold black line show the average retail price for all of U.S.*

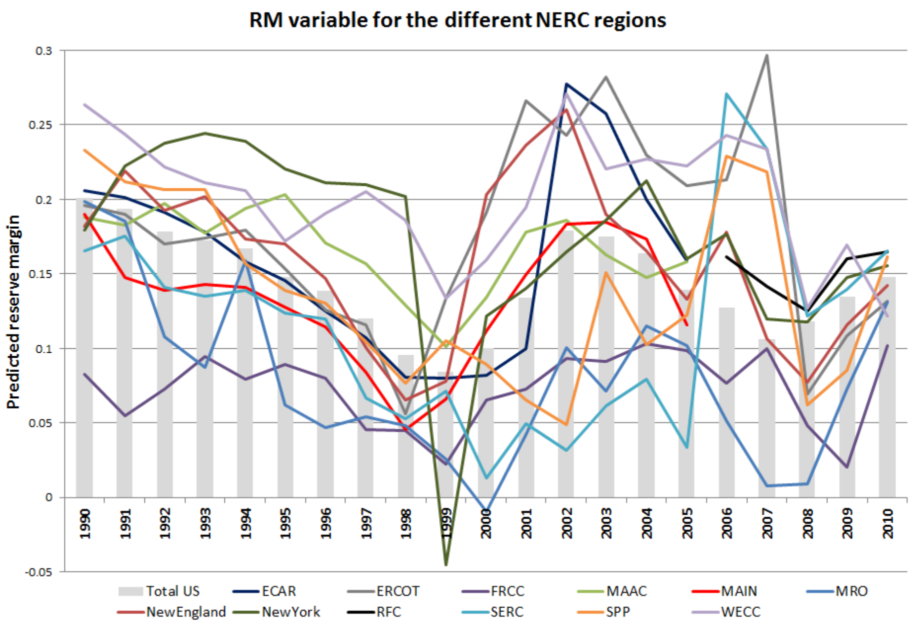



*Figure 10:* *The figure shows the reserve margin predicted in the year $t-1$ NERC Electricity Supply and Demand database for year $t$ for the different NERC-regions. This figure also show the total predicted U.S. reserve margin as grey bars.*

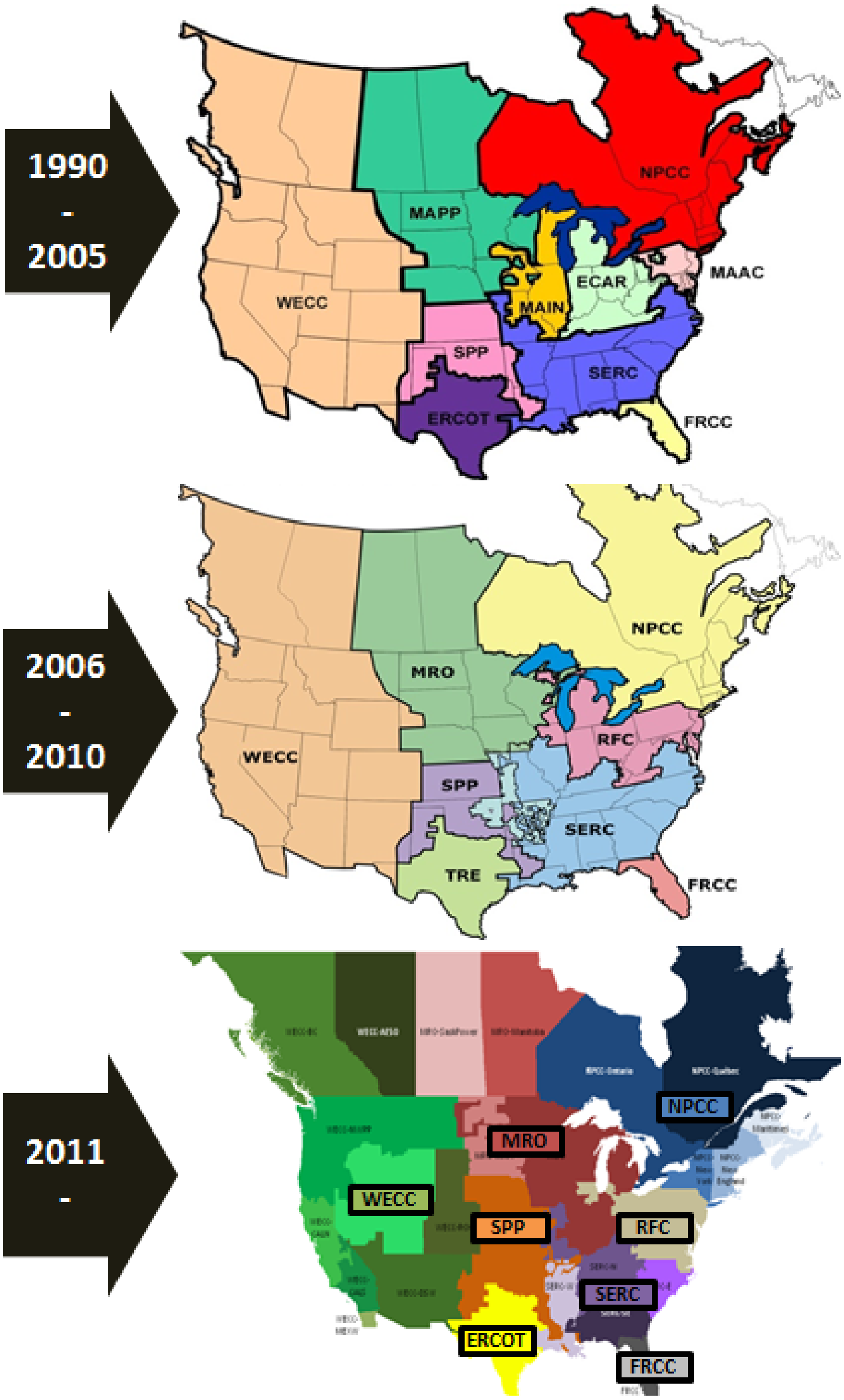



*Figure 11: This Figure shows the development of NERC regions from 1990 to 2014. As NERC-region boundaries change so does the reserve margin variable in our regressions. All maps are taken from the NERC website.*

## A.3 State Level Relative Planned Capacity

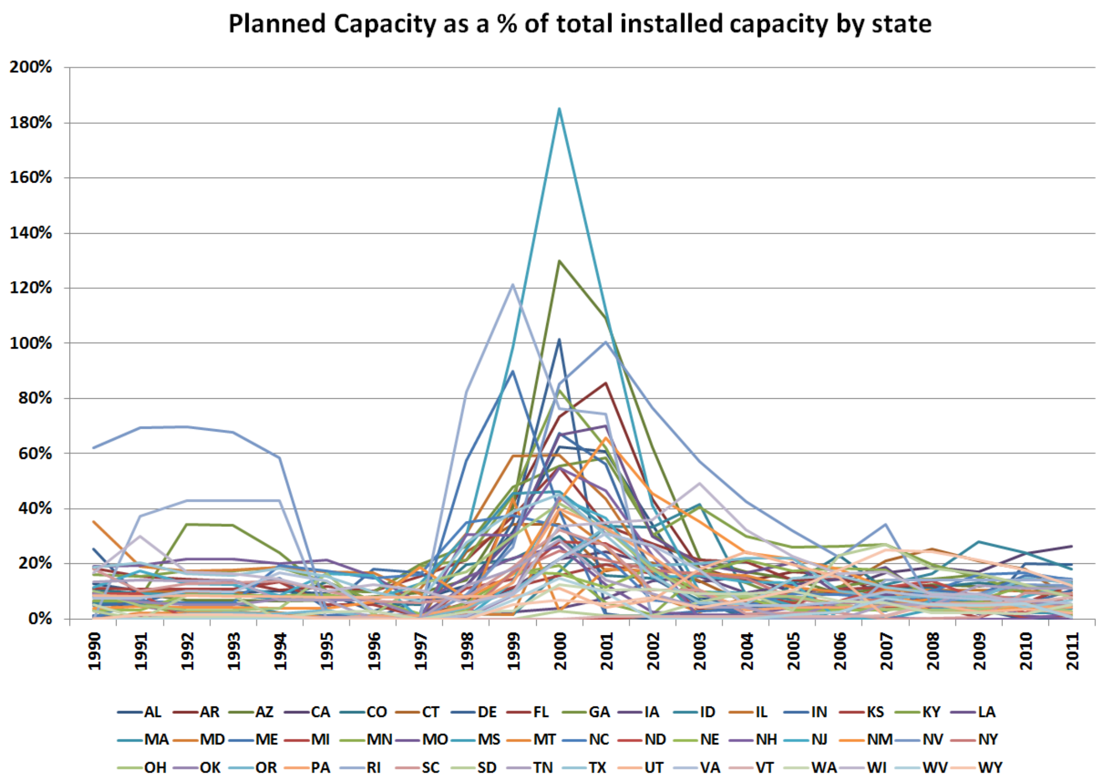



*Figure 12: The figure show the planned capacity as a % of total installed capacity by state in year t. This is an illustration of the PCAP variable used in our regressions.*

## A.4 Regulatory Uncertainty Variable

| | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **AL** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **AR** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **AZ** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **CA** | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **CO** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **CT** | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **DE** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| **FL** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **GA** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **IA** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **ID** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **IL** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **IN** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **KS** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **KY** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **LA** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| **MA** | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **MD** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| **ME** | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **MI** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **MN** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **MO** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **MS** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **MT** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **NC** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **ND** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **NE** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **NH** | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **NJ** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **NM** | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **NV** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **NY** | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **OH** | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **OK** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| **OR** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **PA** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **RI** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **SC** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **SD** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **TN** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **TX** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **UT** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **VA** | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **VT** | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **WA** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **WI** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **WV** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **WY** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

*Figure 13:* *This table show the regulatory uncertainty variable for each U.S. state from 1990 to 2011 included in the regressions. The state abbreviations follow the American National Standards Institute (ANSI) standards. The regulatory uncertainty variable can take on the value of one and zero. REGUNCERT = 1 means the state experience regulatory uncertainty in that year, these cells are marked with a green color. REGUNCERT = 0 means that the state does not experience regulatory uncertainty in that year.*

# B Statistics

In this appendix we define the logistic regression, summarize the variables used and look at various ways of evaluating and testing the full sample regression results.

## B.1 Logistic Regression

The logistic regression function is a non-linear function where the dependent variable can either be one or zero. The probability of the dependent variable being one depends on the independent variables. The logistic regression function as described in Long and Freese (2006) is given by

$$Pr(DV = 1|\mathbf{x}) = F(\mathbf{x}\boldsymbol{\beta}) = \frac{e^{\beta_0 + x_1\beta_1 + \ ... \ + x_8\beta_8}}{1 + e^{\beta_0 + x_1\beta_1 + \ ... \ + x_8\beta_8}}$$

Where DV is the dependent variable (*postponing* = 1 or *canceling* = 1, and *proceeding* = 0), $\beta_0$ is the intercept, $\beta_i$ are the regression coefficients and $x_i$ are the independent regression variables. We use seven such independent variables in our main regression in this paper. All the logistic regression results presented in the tables of Section 4 and 5 are given as marginal effects, which are given by the slope of the probability curve:

$$\frac{\partial Pr(DV = 1|\mathbf{x})}{\partial x_i}$$

For binary independent variables, such as our REGUNCERT variable, marginal effects measure discrete change. That is, how the predicted probability of $DV = 1$ change as the binary independent variable changes from 0 to 1. The marginal effect of continuous variables are likewise interpreted as how the predicted probability of $DV = 1$ change as the continuous variable increases by one unit.[31] The significance of the marginal effect given in the result tables is calculated using a Wald tests. The Wald test assesses whether $H_0 : \beta_i = 0$, where $H_0$ is more likely to be rejected as the Wald statistic gets larger. The size of the Wald statistic increases as the distance between the hypothized values and the estimated coefficients gets larger but also when the curvature of the log likelihood function increases (Long and Freese, 2006).

[31] In reality, the marginal effect for a continuous variable measure the instantaneous rate of change, which may not be the exact effect on $Pr(DV = 1)$ of a one unit increase in the independent variable.

## B.2 Summary Statistics

In Table 13 we present the summary statistics of our entire final dataset, this includes all existing generator-year observations from EIA Form 860 for all the generators that exist in our dataset. More relevant though is Table 14 which includes exclusively the generator-year observations used in our regression analysis.

*Table 13: Summary statistics for independent regression variables for existing generator-year observations from EIA Form 860 for all the generators that exist in our dataset*

| Variable | Observations | Mean | Stdev | Min | Max |
|---|---|---|---|---|---|
| REGUNCERT | 37,821 | 0.14 | 0.35 | 0 | 1 |
| T10 | 37,821 | 4.73 | 1.07 | 3.22 | 8.55 |
| PCAP | 37,821 | 0.18 | 0.20 | 0 | 1.85 |
| RM | 37,821 | 0.14 | 0.07 | -0.05 | 0.30 |
| RHH | 37,821 | 20.5 | 31.7 | -105.7 | 149.1 |
| TG | 37,821 | 7.83 | 14.26 | 0 | 97.00 |
| SIZE | 37,821 | 146 | 113 | 1 | 1379 |

*Table 14: Summary statistics for independent regression variables exclusively for the relevant generator-year observations used in our regression analysis*

| Variable | Observations | Mean | Stdev | Min | Max |
|---|---|---|---|---|---|
| REGUNCERT | 9,886 | 0.25 | 0.43 | 0 | 1 |
| T10 | 9,886 | 5.57 | 1.10 | 3.22 | 8.55 |
| PCAP | 9,886 | 0.27 | 0.27 | 0 | 1.85 |
| RM | 9,886 | 0.12 | 0.07 | -0.05 | 0.30 |
| RHH | 9,886 | 33.9 | 23.6 | -75.6 | 149.1 |
| TG | 9,886 | 3.93 | 10.53 | 0 | 97.00 |
| SIZE | 9,886 | 170 | 122 | 1 | 1379 |

We see from Table 14 that some of the independent variables vary significantly between the different observations. This is especially evident for the firm specific variables such as total number of generators owned by the firm (TG) and the summer capacity of each generator (SIZE), as well as spark spread approximation (RHH). None of these observations are especially surprising as capacity naturally will vary when all gas-fired generators planned in the U.S. are included in the sample. It might seem strange that the minimum value of the TG variable is zero; this is simply because a great number of planned generators are planned by firms who do not yet own a generator. And the generator will not be registered as owned by the firm in the TG variable before it starts operating. RHH naturally varies as efficiency of different generators varies and retail electricity prices vary greatly across the states.

## B.3 Multicollinearity

Table 15 shows the Pearson correlation coefficients for the independent variables presented in a correlation matrix.

*Table 15: Correlations matrix for independent variables*

| | REGUNCERT | T10 | PCAP | RM | RHH | TG | SIZE |
|---|---|---|---|---|---|---|---|
| REGUNCERT | 1.00 | | | | | | |
| T10 | 0.13 | 1.00 | | | | | |
| PCAP | -0.13 | 0.04 | 1.00 | | | | |
| RM | -0.28 | -0.03 | -0.23 | 1.00 | | | |
| RHH | -0.06 | 0.02 | -0.19 | 0.18 | 1.00 | | |
| TG | -0.03 | -0.12 | -0.00 | -0.06 | -0.02 | 1.00 | |
| SIZE | 0.03 | -0.17 | 0.12 | -0.01 | 0.11 | 0.16 | 1.00 |

This correlation matrix is calculated using the same generator-year observations that were used to calculate the summary statistics in Table 14, and therefore exclusively represent the observations used in the regression analysis. There are no problematic correlations between any of the independent variables. According to Eikemo and Clausen (2007) a correlation of at least $\pm 0.8$ is needed in order to cause multicollinearity in the regression results. To be sure we run a simple variance inflation factor test (VIF), using the VIF command in STATA after running an OLS regression on our independent variables. An OLS regression is used because the VIF command cannot be executed after running a logistic regression. Running an OLS regression followed by a VIF command will not change the results because the dependent variable is not included in the multicollinearity (Eikemo and Clausen, 2007). Table 16 show the results from the VIF for both the CANCEL and the POSTPONING regression.

*Table 16: Variance inflation factor test*

| **Variable** | **POSTPONING** | | **CANCEL** | |
|---|---|---|---|---|
| | $VIF$ | $1/VIF$ | $VIF$ | $1/VIF$ |
| REGUNCERT | 1.19 | 0.84 | 1.17 | 0.86 |
| T10 | 1.13 | 0.88 | 1.15 | 0.87 |
| PACP | 1.10 | 0.91 | 1.12 | 0.89 |
| RM | 1.09 | 0.91 | 1.10 | 0.91 |
| RHH | 1.06 | 0.94 | 1.10 | 0.91 |
| TG | 1.06 | 0.94 | 1.08 | 0.93 |
| SIZE | 1.04 | 0.95 | 1.06 | 0.94 |

As we can see no VIF values are higher than 1.19, a cut off value of 10 has been suggested by Kutner et al. (2004). The results are far below this cut off value and hence we discard multicollinearity as an issue in our dataset.

## B.4 Discrimination

Discrimination is a potential problem for logistic regressions; it can happen if we have a bad relationship between the dependent and the independent variables. This phenomenon only occurs for categorical independent variables. We have one such variable, REGUNCERT, which takes on the value of one or zero. We can investigate whether we have discrimination issues in our dataset by making a cross tabulation of the dependent variables and the categorical variable, as we have done in Table 17.

*Table 17: Cross tabulation of dependent variables and REGUNCERT*

| | **POSTPONING** | | **CANCEL** | |
|---|---|---|---|---|
| | $POSTPONING = 1$ | $POSTPONING = 0$ | $CANCEL = 1$ | $CANCEL = 0$ |
| REGUNCERT = 1 | 1,183 | 818 | 419 | 818 |
| REGUNCERT = 0 | 3,216 | 3,186 | 1,064 | 3,186 |

The source of discrimination troubles stems from the fact that logit is calculated as the natural logarithm of the odds ratio. For instance had there been zero observations of REGUNCERT = 1 when CANCEL = 1 then the odds ratio would be zero for the case when generators get cancelled under regulatory uncertainty. This would make the logistic coefficient equal to $ln(0) = -\infty$ because REGUNCERT= 1 is a reference category. The interpretation of the REGUNCERT variable would then be meaningless (Eikemo and Clausen, 2007). We see that this is not an issue in our study as we have a sufficient number of observations in all categories in order to calculate and compare meaningful odds ratios and the natural logarithms of these.

## B.5 Hosmer-Lemeshow Test

The Hosmer-Lemeshow (H-L) test is a goodness of fit test for logistic regression models. The test assesses whether the regression model fits the observed events. It is different from Pearson's $\chi^2$-test commonly used on linear regressions, in that it identifies subgroups of the model population and form categories for the continuous variables. Observations are sorted into groups of increasing order of estimated probability of having an event occur. The observations are then divided into equal sized groups. The H-L statistics are acquired from STATA using the command **estat gof, group(10)**, where group(10) is used in order to specify the number of groups we want constructed. Ten groups are standard when using the H-L test. The results of this test for the main regressions are presented in Table 18.

*Table 18: Results of Hosmer-Lemeshow test on both logistic regressions*

| | POSTPONING | CANCEL |
|---|---|---|
| No. of Observations | 8,403 | 5,487 |
| No. of Groups | 10 | 10 |
| Degrees of freedom | 8 | 8 |
| Hosmer-Lemeshow $\chi^2$-Statistic | 15.28 | 70.56 |
| $Prob > \chi^2$ | 0.0539 | 0.0000 |

A logistic model is said to fit if the data if the p-value of the H-L statistic is higher than 0.05. This is when we fail to reject the null hypothesis that there is no difference between the observed and model-predicted values. As we see in Table 18 this is not the case for the CANCEL regression. Here the statistic is high and the p-value is 0.000. For POSTPONING on the other hand we can accept the null hypothesis and say the model fits the data.

Any goodness of fit test is primarily concerned with the predictive power of the model, which is not the primary goal of our study. As we indicate in the result section of this paper and in Appendix B.1, our main focus is studying the marginal effects of the logistic regression coefficients in order to evaluate how the various independent variables affect investment behavior. The model will not explain everything. With our large dataset, only seven independent variables, a binary dependent variable, lumpy occurrence of events and no interaction variables it is natural that the fit is not very good. Especially the lumpy nature of canceling, with 53 % of observations in 2001 and 2002, could significantly impact the model fit. Addressing some of these factors may be relevant in future research. To create a better fitted model, including interaction variables and a variable that more closely captures the profitability outlook for generator investment would be a start.

A large goodness of fit statistic indicates there is some lack of fit, but provides no insight about its nature. A disadvantage of the H-L test is that it can only tell us if a model is significant or not, but nothing about the extent of the fit. Similarly this test is strongly influenced by the sample size. In large samples, such as the ones we are using here, just very small differences could lead to significance. As the sample size gets larger, the H-L statistic can identify smaller and smaller differences between observed and model-predicted values to be significant. Therefore, with samples of our size it is hard to find models that are parsimonious (i.e. that use the minimum amount of independent variables to explain the dependent variable) and fit the data (Agresti, 1996).

## B.6 Classification Table and the receiver operating characteristics curve

Classification table is a test of the logistic regression model's ability to predict the observed values. This table show how observed values coincide with the predicted probabilities of our model. The probability of the dependent variable being equal to one is calculated by using the values of the independent variables for each observation used in the regression. A cut-off value of 0.5 is used, this means that if e.g. $Prob(POSTPONING = 1) > 0.5$ for a specific observation then the predicted value for POSTPONING for that observation is set to 1. Table 19 shows the classification tables for the POSTPONING regression and Table 20 show the classification table for the CANCEL regression.

*Table 19: Classification table for the POSTPONING regression*

| **Predicted** | **True POSTPONING** | | **Total predicted obs** |
|---|---|---|---|
| | $POSTPONING = 1$ | $POSTPONING = 0$ | |
| POSTPONING = 1 | 3,055 | 1,734 | 4,789 |
| POSTPONING = 0 | 1,344 | 2,270 | 3,614 |
| Total true obs | 4,399 | 4,004 | 8,403 |
| Sensitivity | 69.45% | | |
| Specificity | 56.69 % | | |
| Correctly classified | 63.37 % | | |

*Table 20: Classification table for the CANCEL regression*

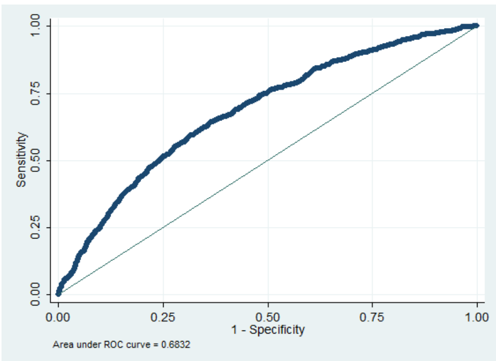
| **Predicted** | **True CANCEL** | | **Total predicted obs** |
|---|---|---|---|
| | $CANCEL = 1$ | $CANCEL = 0$ | |
| CANCEL = 1 | 186 | 129 | 315 |
| CANCEL = 0 | 1,297 | 3,875 | 5,172 |
| Total true obs | 1,483 | 4,004 | 5,847 |
| Sensitivity | 12.54 % | | |
| Specificity | 96.78 % | | |
| Correctly classified | 74.01 % | | |

The overall rate of correct classification is estimated to be 63 % for the POSTPONING regression model. Sensitivity is the fraction of observed-positive outcome cases that are correctly classified; specificity is the fraction of observed negative-outcome cases that are correctly classified. The sensitivity of the POSTPONING model tells us that 69 % of observed postponings were correctly classified by the model. The specificity of the POSTPONING model tells us that 57 % of observed proceedings were correctly classified by the model.

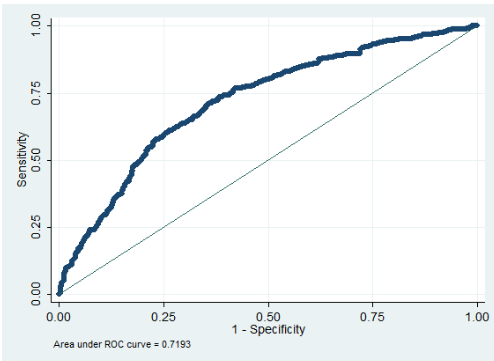
Likewise the overall rate of correct classification is estimated to be 74 % for the CANCEL regression model. The sensitivity of the CANCEL model tells us that 13 % of observed cancellations were correctly classified by the model. The specificity of the CANCEL model tells us that 97 % of observed proceedings were correctly classified by the model. The low sensitivity of the CANCEL regression can be explained by the low number of CANCEL observations versus proceeding observations, hence the probability of canceling will naturally be low and the cut-off boundary harder to achieve, unlike the POSTPONING case where we have almost an equal amount of observations. Another reason for why the model fails to correctly classify a large number of cancellations could be due to the variability and lumpiness of the cancellation observations where 53 % of all cancellations occur between 2001 and 2002. This could significantly impact the value of the regression coefficients and hence be responsible for the model's lack of predictive power on cancellation. In return the model has a very good predictive power for proceedings.

We also graph the $sensitivity$ versus $(1 - specificity)$ as the cut-off value is varied in Figure 14. This is called the receiver operating characteristics curve (ROC curve). On such a curve a model with no predictive power would be a 45°line, the greater the predictive power of the model the more bowed the curve and the greater the area under the curve. A model with no prediction has an area under the curve of 0.5 and a perfect model has an area of 1.

*Figure 14: ROC plots*



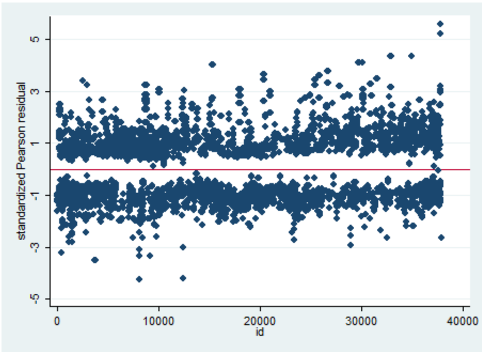

(a) ROC plot for the POSTPONING regression



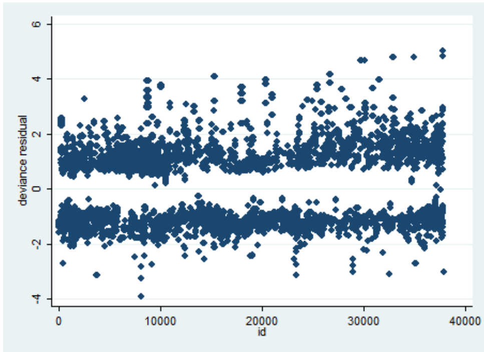

(b) ROC plot for the CANCEL regression

Our area under the curve is 0.68 for the POSTPONING model and 0.72 for the CANCEL model. These values tell us that our models yield a fair predictability and are more likely to correctly predict investment behavior than a random model.

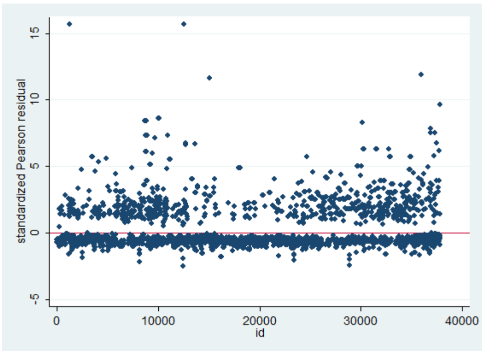
## B.7 Residual Plots



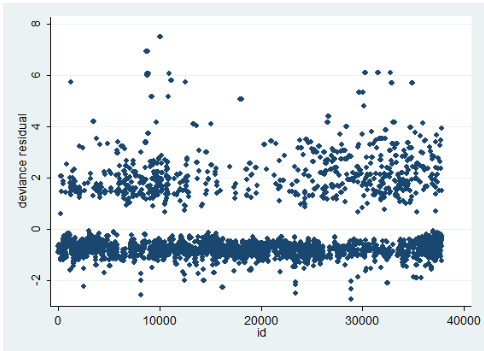

(c) Pearson residual plot for POSTPONING regression




(d) Deviance residual plot for POSTPONING regression




(e) Pearson residual plot for CANCEL regression




(f) Deviance residual plot for CANCEL regression

*Figure 15: Pearson and Deviance residual plots for POSTPONING and CANCEL regressions*

The Pearson residual measures the relative deviations between the observed and fitted values. The deviance residual measures the disagreement between the maxima of the observed and the fitted log likelihood functions. Interpreting residual plots for logistic regressions is not the equivalent of interpreting residual plots for linear regressions. A linear regression assumes homoscedasticity (equal error variance for all values of the criterion) while the logistic regression assume heteroscedasticity (differing error variance for each value of the predicted score) (Cohen et al., 2002).

The residual plots for logistic regressions could help us identify outliers, these outliers could then again help us understand if we have misspecified some variables in our model. From Figure 15 we can see that the residuals from the POSTPONING regression are fairly evenly distributed, while the CANCEL residuals have a wider distribution on the positive side of the y-axis. These outlying observations could hold the key to why we are experiencing a worse fit for the CANCEL model than that for the POSTPONING model. The CANCEL residuals with a high positive value could also be a natural result of how the residuals are calculated. The prediction of CANCEL = 1 will naturally be low for the entire sample as we have a much higher representation of proceedings than cancellations in the CANCEL regression. As was also seen in Appendix B.6. This fact could cause the occasional observations with CANCEL = 1 to have a low predictability of cancellation which would lead to a very high Pearson residual value.[32] This is also why we don't see similar residual jumps below the x-axis.

[32]This is evident by looking at the way Pearson residuals are calculated $r_P = \frac{observed-expected}{\sqrt{expected}}$