A Time Series Analysis of Drivers for Switching in Peak Power Plants

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Abstract

This paper examines the characteristics of two stochastic processes that acts as drivers for the switching between operating states in peak power plants. These drivers are the projected reserve margin and regulatory uncertainty. Useful representations for each driver are constructed in reduced form. I find that the projected reserve margin is best fitted as an AR(1) model. Regulatory uncertainty exhibits many features consistent with a standard Markov Chain model. However, I find that the data on regulatory uncertainty can better be explained by treating the transition probabilities of the Markov Chain as time-variant. I construct these dynamic probabilities by mathematically quantifying diffusion - the tendency for new ideas to spread across groups - in policy innovations between U.S. states. The investigation utilizes data from most of the continental U.S. power industry in the period 1990-2011, although its primary results and focus are on wholesale electricity markets PJM, NYISO and NEISO in the Eastern region.

Keywords: Real options, Energy markets, Time-varying Markov Chain, Projected reserve margin, Regulatory uncertainty

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1 Introduction

Peak power plants are flexible generators that produce electricity only during times of peak demand or shortfall of base capacity. Since electricity cannot be stored and its demand varies greatly, such plants are crucial for the reliable operation of any power market. This paper investigates thermal peak plants, which produce electricity through the consumption of fuels. Such plants have the highest operating costs in the market, which causes them to only produce in discrete short periods when the price of electricity is sufficiently high. Consequently, peak plants remain idle for the majority of the time[1].

Maintaining a peak plant's ability to initiate production on short notice is expensive. Thus, if a plant expects it to be a long time until next price spike, it can reduce these costs by lowering this capability. This is referred to as entering into a stand-by or mothballing state, in which maintenance costs are reduced by letting go of most of the employees and terminating contracts with suppliers. Generally, a peak plant can be in one of three *operation states*, defined as

- Operating state (OP): the plant can initiate production on short notice, whilst holding the option of entering the stand-by state for an irreversible one-time investment cost.
- Stand-by state (SB): the plant cannot initiate production, but holds the option to re-enter the operating state for an irreversible one-time investment cost.
- Retirement state (RE): the plant is abandoned and cannot become operational again.

The possible transitions between these states are illustrated in Figure 1. The managerial decision of deciding when to switch between these states constitute the *switching problem.*

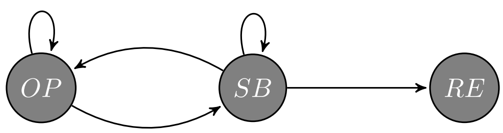


Figure 1: State Diagram for Peak Plant Switching
A peak plant can either be in an operating state (OP), stand-by state (SB) or retirement state (RE). A plant cannot return from the retired state.

This switching problem can be described by the theory of real options. Pioneered by the works of Brennan and Schwartz (1985) and McDonald and Siegel (1987) and largely institutionalized in Dixit and Pindyck (1994), real option theory describes how the the ability to postpone an irreversible investment has a tangible value given that the future outcome is uncertain. This contradicted the then widely accepted net present value approach by Bierman Jr and Smidt (1960), which only considered a now-or-never approach to investment. Numerous theoretical applications of the theory have since been developed in the literature, however, despite its academic popularity there have been relatively few empirically documented cases that suggests that firms actually implement this valuation technique in practice (Kellogg, 2014), even though this should provide a competitive advantage over other firms. Several studies that surveys firm managements directly, like Graham and Harvey (2001) and Triantis (2005), find that very few companies formally use real option techniques in their investments decisions. Yet, the actual investment decisions made by firms in many industries are largely consistent with real option theory, as suggested by the investigation made by Gunther McGrath and Nerkar (2004) for the pharmaceutical industry and Kellogg (2014) for the the Texas oil drilling industry. This discrepancy is generally explained by how firms tends to use "rules of thumbs" (e.g. Mcdonald, 2000; Chittenden and Derregia, 2013) or simple "heuristics" (Kellogg, 2014) to mimic real option valuation techniques and thus achieving close-to-optimal

[1]Kehlhofer et al. (2009) defines peak plants as generators producing less than 23% of the time. Available data of electricity and fuel prices suggests that most peak plants have an average operational time much lower than this.

results. Nevertheless, the discrepancy itself warrants motivation for additional empirical studies both to confirm the presence of real option effects in firm's decision-making, as well as to uncover how they are actually implementing such techniques.

Real option effects specifically related to peak plants in the U.S. power industry have been investigated by several authors. Fleten et al. (2012) investigated the switching problem as defined above for 1,121 individual power plants for the period of 2001-2009. They evaluated the effect of seven drivers on the switching decisions; the projected reserve margin, the ten-year treasury rate, the efficiency of the plant, the capacity (size) of the plant, the total capacity owned by the plant owner, the spark spread volatility and regulatory uncertainty. They found all drivers to be significant in the switching decision, where the latter two indicate strong real option effects. This research was extended by Fleten et al. (2014), who found specific estimates of the irreversible costs of the switching using non-parametric structural estimation. A different but related real option problem was also investigated empirically by Kaldahl and Ingebrigtsen (2014) whom found significant real options effect in the same peak plant owners' sequential investments when building the plants in the first place. This implies that these utility owners might be a group that is particularly susceptible for using real option theory in their strategic decision-making.

A greater insight into this switching problem in the framework of real options requires in-dept understanding of the underlying drivers to the switching identified by Fleten et al. (2012). For this purpose, particularly two of the factors they identified stand out as interesting for further analysis. These are the projected reserve margin and regulatory uncertainty. These are both exogenous from the perspective of the plant managers, they behave stochastically over time and there is to my knowledge little existing literature on the behaviour of these processes.

The purpose of this paper is thus to illuminate the nature of these two processes. Specifically, I attempt to replicate their behaviour by constructing representations of each driver in reduced form, as well as discussing their impact on the switching problem and each other.

As Fleten et al. (2012), I am considering plants located in three specific wholesale electricity markets, the Pennsylvania-New Jersey-Maryland (PJM), the New England Independent System Operator (NEISO) and the New York Independent System Operator (NYISO)[2].

The remainder of the paper is structured as follows. In Section 2 I provide institutional context and definitions of the drivers. Independent time series analyses then follows for the projected reserve margin in Section 3 and for regulatory uncertainty in Section 4. Section 5 offers a discussion on how the drivers influence each other. The main conclusions are summarized in Section 6.

[2]See Figure 12 in Appendix A for details.

2 Institutional Context and Description of Drivers

2.1 U.S. Power Market and Institutions

The U.S. power market is a complex system with many different stakeholders, regulatory entities and institutions that sometimes experience functional overlaps. While both public and privately owned individual utilities provide generation and distribution, larger independent organizations control the transmission lines and individual power markets.

The Federal Energy Regulatory Commission (FERC) is an independent non-for-profit institution which oversees and regulates the interstate transmissions of electricity, natural gas and oil. It oversees seven Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs), two similar types of organizations which controls and operates the electrical power system in a particular area. These seven entities constitutes seven of the ten power markets in the United States.

The North American Electric Reliability Corporation (NERC) is another non-profit organization which in many ways operates in parallel to FERC. It is responsible for improving the reliability and security of the bulk power system, it develops and enforce standards for power system operation monitoring and assess resource adequacy. It is associated with nine Regional Reliability Councils, which are similar but not identical to the ISOs/RTOs associated with FERC, which is sometimes a cause for confusion. A major part of NERC's responsibility lies in assembling information and performing reliability analyses.

The U.S. Energy Information Administration (EIA) is a federal agency associated with the U.S. Department of Energy. It is responsible for collecting and analysing data related to energy in the interest of promoting sound policymaking.

NERC annually publishes an Electricity Supply Demand (ESD) database with comprehensive information about the U.S bulk power system, including ten-year forecasts. I will use data from this publication in my analysis.

2.2 Impact of Status Changes Data

There is a practical time lag in the transition of a switch, particular when going from the mothballing state back to the operating state, as it takes time to rehire workers and renegotiate supplier contracts. That means that the implications of the switch are set for a certain period into the future, which is why switching to another operating state is a *current* decision that determines the plant's *future* ability to produce and earn cash flows.

In practice, this time lag is in the order of a couple of months (Fleten et al., 2012). However, to the best of my knowledge, the only available data on such status changes comes from Form 860 collected by the EIA. This form is annually collected from the plants, and include a single operating status for that given year. Therefore, empirical studies of the switching problem can only be performed on an annual basis. Even though I do not use the switching data directly in my analysis, its format carries substantial impacts in how I can model the drivers. This is because both the switching data and the drivers must be modeled on the same time frame if they are ever going to be used in conjunction. For that reason, it only makes sense to model the annual equivalents of the drivers.

The first, and perhaps the most significant, consequence of the format is that it reduces the number of observations of the driver data, since much data must be aggregated from daily observations. From a time series analysis perspective, this severely reduces the amount of information available to estimate the parameters of the models. Thus, the uncertainty of the analysis will increase, and conclusions will be harder to draw from the data alone.

Secondly, it lays the ground for how I can perceive the timeline of the switching problem. In reality, the plant manager[3] has a daily (more or less continuous) option to initiate a switch. The plant manager will base his decisions on projections and information available for a forward time period stretching at the minimum up until the time lag of the switch (when considering switches between OP and SB) and much further into the future when considering retirement of the plant. However, in order to adapt to the data format I will consider a simplified perspective of this timeline as illustrated in Figure 2.

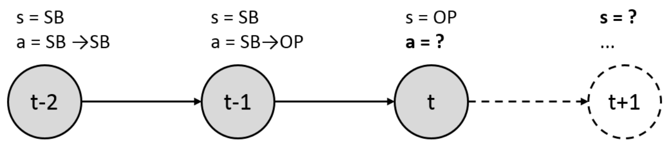


Figure 2: An Annual Timeline for the Switching Problem
Illustrative representation of the simplified switching problem defined on a discrete annual basis. It is assumed that a plant manager in year t, based on available information up to and including that year, make an action a that determines the operation status of the plant in year $t+1$.

I will assume that the plant manager performs the switching decisions at discrete times on an annual basis. It is assumed that the plant manager will have available in year t all past information up to and including that year. Further, I will assume that any decision to switch will not change the operation status of the plant until in the next annual period. Thus, in this perspective, the plant manager makes an action every year to either *shut down* ($OP \rightarrow SB$), *start up* ($SB \rightarrow OP$) or *abandon* ($SB \rightarrow RE$) the plant, or to remain in the current state.

It is fair to assume that for the plant manager, the most relevant future projections with regards to startup and shutdown decisions are those for the coming period $t+1$. For abandonment decisions, however, a longer time perspective would be necessary.

2.3 Driver 1: Projected Reserve Margin

Since electricity must be consumed at the same time as it is produced, the power grid must have more generating capacity available than contemporaneous demand in order to guarantee delivery of electricity and thus prevent blackouts. The measure of this surplus of capacity is called the reserve margin. Seen in the light of supply and demand theory, the reserve margin becomes an indicator of the price of electricity. Since peak plant switching aims for the plant to be in the operating state (OP) when electricity prices are high, the *projected* (i.e. future) value of the reserve margin becomes a clear driver for the switching process.

The reserve margin is known by various definitions in the literature. I use the same definition used by Fleten et al. (2012) and Billingsley and Ullrich (2011).

Definition: The projected reserve margin for region r in year t is given by

$$RM_{r,t} \equiv \frac{(C_{r,t} - D_{r,t})}{D_{r,t}} \tag{1}$$

where the $C_{r,t}$ represents the planned capacity for electricity generation and $D_{r,t}$ represents the

[3]In this context, I will use this term to denote the individual or individuals responsible for making switching decisions.

projected peak demand for electricity in region r in year t[4].

The data for the demand for and capacity of electricity comes from the ES&D database[5]. This database contains data on numerous factors that describe the bulk power system (BPS) in the U.S, including historical values with ten-year projections. Its projected capacity data is based on reports collected from all plant owners concerning their planned capacity for the future.

As I have defined the timeline of the switching problem in Figure 2, the relevant information needed to make the switching action at time t is information available at time t that illuminates the conditions at time $t+1$. Since it likely takes time for the EIA to collect and assemble the data for their database, the data published in year t is probably collected closer to year $t-1$. Therefore, the data that best describe the conditions at time $t+1$ is the two-year forward projection. This projection is thus what I investigate as a driver for switching in my analysis.

From the perspective of a peak power plant, a low two-year projected reserve margin in year t will indicate that the market might experience shortage of capacity and thus high prices in year $t+1$, creating incentives for the peak plant to switch to the operating state (OP) at time t.

2.4 Driver 2: Regulatory Uncertainty

Traditionally in U.S. power markets, power generators have acted as natural monopolies where consumers only had the option to purchase electricity from their local producer. This changed however, with the introduction of retail competition in certain U.S. states starting in the early 1990s. This is generally referred to as deregulation or restructuring. Under retail competition, existing utilities may loose (gain) customers to (from) competing utilities with lower (higher) cost of generation (Wangensten, 2011). Uncertainty related to whether or not such retail competition are going to be implemented is thus equivalent to uncertainty of future demand. According to real option theory, such regulatory uncertainty should influence investment decisions in peak plants and thus be a relevant driver for switching.

How to measure regulatory uncertainty is not standardized, though most literature use some form of binary indicators constructed on the basis of qualitative information. The methodology used in constructing these variables differ substantially though. Fabrizio (2013) found evidence in support of firms investing less in new renewable generation assets in U.S. states with regulatory uncertainty. Her proxy variable is defined based on whether or not the state has passed and repealed deregulation in the electricity industry. Ishii and Yan (2004) on the other hand constructs a set of three binary variables defined by how many years the state is into the process of passing deregulation. This method thus grades the uncertainty by these three proxies, following the argument that the the uncertainty of the outcome of the deregulation process should be greatest the first year after initiation and at its lowest right before the bill is passed or not.

However, the proxy for regulatory uncertainty that I will consider began with the work of Billingsley and Ullrich (2011), who considers a regulatory uncertainty proxy based on a Retail Competition Index. This index describes the process of implementing deregulation in five steps, illustrated in Table 1. The index was fitted to descriptive data describing the status of deregulation policies for individual states from the EIA[6]. Fleten et al. (2012) extends this representation of the regulatory uncertainty based on this index, by constructing a binary regulatory uncertainty proxy that takes the value of 1 if a state is in step 2 or 3 of the Retail Competition Index in a given year, and 0 otherwise. Their uncertainty variable thus defines a U.S. state to experience regulatory uncertainty if that state has initiated the deregulation process political level but not decided to implement it yet. This approach was further developed Kaldahl and Ingebrigtsen (2014), who used the same proxy

[4]Since the annual U.S demand peaks during the summer, I use the total capacity and peak hour summer demand to calculate the reserve margin.

[5]The database is available at NERC (2014a).

[6]Available at EIA (2015).

as Fleten et al. (2012) but additionally considered the consequences of U.S. states experiencing unusually high or low retail electricity prices[7], which they filtered out from the data.

Table 1: Retail Competition Index
Index depicting the steps involved in the transition from a regulated to a deregulation retail electricity market as developed by Billingsley and Ullrich (2011).

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

Kaldahl and Ingebrigtsen (2014) presents their final results of the proxy variable in time series form for the 48 mainland U.S. states from 1990 to 2011. I find these results valuable as they are the result of an iterative process that has improved this proxy for regulatory uncertainty over several papers. Additionally, Billingsley and Ullrich (2011), Fleten et al. (2012) and Kaldahl and Ingebrigtsen (2014) have all found variations of this proxy influential in firms' decision-making on capital investments, which confirms its usefulness.

For these reasons, I perform my analysis of the characteristics of the regulatory uncertainty directly based on the data from Kaldahl and Ingebrigtsen (2014).

Definition: Thus, regulatory uncertainty associated with the introduction of retail competition is represented by the binary proxy

$$REGUNCERT_{s,t} \in [0,1]$$

which is equal to 1 if there are regulatory uncertainty in present in year t in U.S. state s, and 0 otherwise.

[7]One of the main motivations for implementing retail deregulation was to lower the price of electricity for consumers. High retail prices could thus act as a driver for regulatory uncertainty.

3 Projected Reserve Margin

The following section contains an independent analysis of the projected reserve margin. The analysis is rooted in a statistical investigation of the historical data, though the results are evaluated by reviewing the process in an economic context.

3.1 Stakeholders Influencing the Reserve Margin

The RM is by definition a fraction of excess capacity over peak demand, which place certain limits on how far its value might deviate over time. This suggest that the process probably is stationary in mean. Also due to the implications of it becoming negative, it is likely that the reserve margin will be predominately positive over time.

As a process, the RM is influenced by the factors and stakeholders that affects the total capacity and the peak demand in the system. These can be categorized into three main "forces".

The first relates to the projected peak demand. Generally, this is significantly more stable than actual peak demand. Actual peak demand is heavily influenced by weather conditions, in the way that a hot summer day creates incentives for additional air conditioning. The projected demand, however, is set for a particular temperature (a constant expected value) which eliminates this source of random interference. Therefore, the projected demand is more influenced by changing demand due to factors like the performance of the overall economy. For this particular analysis, changes in the economy and other influences to the projected peak demand can largely be thought of as exogenous, and thus, for simplicity, as a "random" influence to the RM.

The second influence on projected reserve margin is through the projected capacity, which is primarily determined by the individual generators themselves and how they report their plans for the future. If it is assumed that these generators (whether privately or publicly owned) act rationally with the intentions of maximizing profits, then they represent a force controlled by market conditions that influence the RM.

The third and final influence on the RM are the grid operators responsible for maintaining the reliability of the power system. Since blackouts and disruptions to the energy flow have drastic consequences for the society, these entities have a definite influence on the capacity. This control is exerted in two possible ways. In order to maintain reliability on a continuous level, separate capacity markets exists where generators receive payments simply for having capacity available to enter into the grid on short notice, for example in the form of spinning reserves. This is an influence based on incentives and market conditions, where the grid operator purchase the power. The other way grid operators can affect the capacity is through executive actions out of concerns for the reliability of the power flow. For example, if the capacity lost by a peak plant considering to enter the mothballing state is critical for the system, the operator can force the plant to remain in the operating state through the use of "Reliability Must Run" agreements (NERC, 2009).

As such, the three main forces driving the projected reserve margin process are exogenous/random factors like the overall state of the economy, market-oriented generators and balance-responsible grid operators.

3.2 Specifying the Data

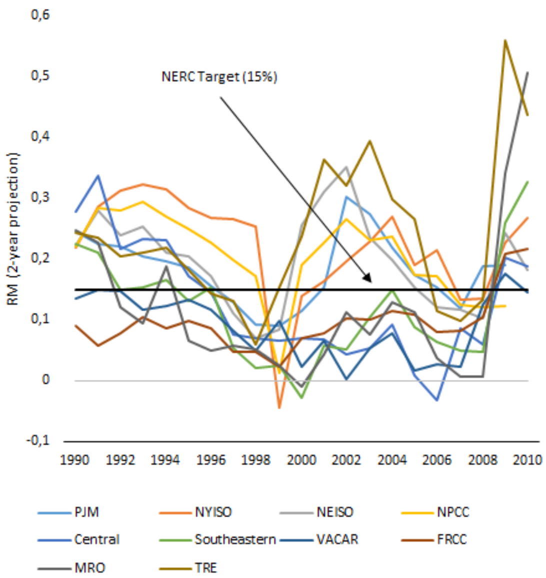
The projected reserve margin data from the ES&D database is available at NERC region level from 1990-2010, which is the sample period I am considering for this driver. For time series analysis, 21 observations is a low number which poses challenges when trying to get sound statistical results. For that reason, I utilize data from more regions than the three primarily under consideration

(PJM, NYISO and NEISO) in order to improve the results of the analysis. More data is helpful in analysing the primary regions, since it is reasonable to assume that the projected reserve margin follows the same underlying time series model in all regions even though the parameters of each region probably will differ. Thus, I can use data from other regions to help identify which type of model to use for the PJM, NYISO and NEISO regions, while estimating their parameters based on their own data.

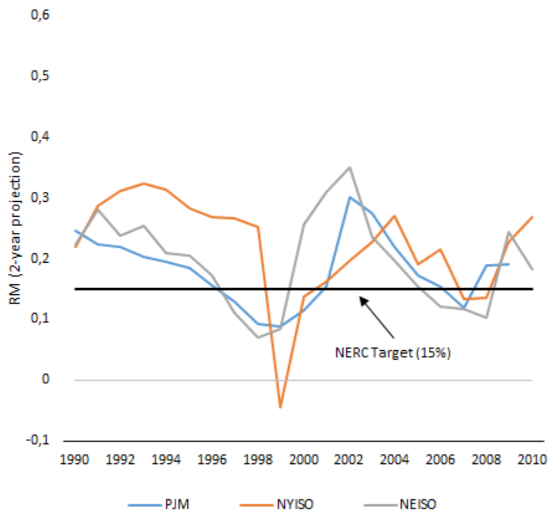
The ES&D database contains data for the capacity and peak demand for 28 individual NERC regions/subregions. However, many of these regions have undergone significant border changes over the course of the sample period[8]. Consequently, their respective data from the ES&D do not represent coherent time series and are thus ineligible for this analysis. Thus, I have selected data for ten regions where the boarder definitions have changed the least over the sample period, and will use these to identify an appropriate model type.

3.3 Visually Examining the Data

All time series analysis starts by examining the data for key characteristics. Together with intuitive knowledge of the underlying process, this often serves as good starting point for finding an appropriate time series representation of the data. This method is particularly useful to identify characteristics when few observations are available, as many statistical tests can give conflicting or inconclusive results for small samples. The ten time series for the selected regions are illustrated in Figure 3a, next to the three regions of primary interest in Figure 3b.



(a) All regions included in the analysis



(b) The three regions of primary interest

Figure 3: Reserve Margin
Historical values for the 2-year projection of the reserve margin per NERC region.

Figure 3a indicates that most regions appear relatively stationary in mean over time[9]. This feature

[8]The most dramatic changes occurred after 2011, when NERC began categorizing the ES&D data by the newly formed Assessments Areas (which are more aligned with ISO/RTO boarders) as opposed to the previous Region/-Subregion definitions (NERC, 2014a). For this reason, this paper only utilize ES&D data up until 2010.

[9]The exceptions are the TRE (formerly known as ERCOT) and MRO regions, which have extremely high projections for 2009 and 2010. Possible explanations could be significant drops in projected demand in both regions due to the economic slow-down following the financial crisis (NERC, 2009), as well as and severe drought (severe increase actual demand, could lead to increase in planned capacity) in TRE in 2010 (NERC, 2010) and significant increase in wind capacity in MRO in 2009.

is consistent with the intentions of both stakeholders capable of influencing the projections. For a plant manager, low projected reserve margins is a signal of potentially high prices in the following time period. This creates incentives for peak plants to switch to the operating state (OP), thus increasing the capacity and the reserve margin for the following period. Conversely, high projections for the reserve margin is an incentive for a plant manager to switch to the stand-by state (SB) or retirement state (RE), creating the opposite effect. This mean-reverting effect indicates that the time series should revert around some mean. The grid operator has similar incentives. Low reserve margins are dangerous for the reliability of the system, while unnecessarily high reserve margins indicate resources being under-utilized, which the operator will not want to pay for. Thus, both of these participants contributes to a mean-reverting characteristic for the projected reserve margin.

Also, the (assumed) constant mean level seems to be close to or slightly above the NERC Target level for the reserve margin of 15% [10] [11], particularly for the three regions of primary interest as illustrated in Figure 3b.

There are indications of time-varying volatility over the sample period for certain regions, illustrated by the dramatically low projection for NYISO in 1999 and correspondingly high projections for TRE/MRO in 2009-2010. Such time-varying volatility is normally modelled with an ARCH/-GARCH representation. However, these are few observations in an already small sample, and the statistical foundation for developing such a model is little if any. Thus, I make the assumption that the underlying projection for the RM has a time-invariant volatility. The implications of this is assumption is that simulations of the process should experience less value spikes than the original data.

3.4 Choice of Model

Given the assumptions that the time series are second-order weakly stationary[12] a representation belonging to the time series class AutoRegressive Moving Average (ARMA) seems to be appropriate for the RM.

In order to identify the orders of the autoregressive and moving average terms p and q of an ARMA(p,q), I estimate the sample autocorrelation function (ACF) and the sample partial autocorrelation function (PACF) of the time series. By comparing the sample ACF and PACF of a time series to the theoretical ACF and PACF of known time series, it is possible to obtain reasonable guesses of the values for p and q. This approach well-known in time series analysis (e.g. Wei, 2006), and particularly suited when the number of expected parameters of the time series representation is small. It is reasonable to assume that the amount of information present in only 21 observations is only sufficient to estimate a relatively small number of parameters. This assumption is supported by the result of the ACF-PACF-Test[13], as shown in Table 2. The test indicate that the sample ACF and PACF of 6 out of 10 time series corresponds to an AR(1) model, while 3 out of 10 were likely either corresponding to an AR(1) representation or an ARMA(p,q) representation where both p and q are higher than 0. Thus, the results from this test indicate strongly that an AR(1) model would be best suited to represent the data, all regions considered. However, as mentioned, this result could be have been influenced by the low number of observations. In addition, since the ACF-PACF test is a subjective test[14], it is prudent to also consider some neighbour models during the parameter estimation.

[10] The NERC Reference Reserve Margin is a target level determined by a region's generation, load, transmission characteristics and regulatory requirements. This can be interpreted as the minimum level of planned reserve margin needed to ensure operational stability of the region's power system. If not set by the region itself, NERC assigns a 15% reserve margin for power system dominated by thermal systems (NERC (2014b)).

[11] Note, since there exist different versions of the reserve margin, this number might not directly comparable with the series in the figure. However, it should work as an approximation the target.

[12] Both mean and variance are time-invariant.

[13] Note that finding the sample ACF of a time series is equivalent to running a test for the detection of autocorrelation, like the Durbin–Watson test or the Breusch–Godfrey-Bertolo test.

[14] It is based on subjectively identifying theoretical characteristics of the ACF and PACF in sample plots.

Table 2: ACF-PACF-Test for Reserve Margin
Reasonable guesses for the specification of p and q. The test indicates that for the majority of the regions, an AR(1) representation is preferred. Unclear results indicate that the indicated model is either an AR(1) model or an unspecified model with unknown positive values for p and q. Details of the test and the plots of the sample ACFs and PACFs for the regions PJM, NYISO and NEISO are illustrated in Figure 13 in Appendix B.

Region	Model indication	Comment
PJM	AR(1)	
NYISO	ARMA(p,q)/AR(1)	Unclear results
NEISO	AR(1)	Probably under-parametrized
NPCC	AR(1)	
Central	AR(1)	
Southeastern	ARMA(p,q)/AR(1)	Unclear results
VACAR	AR(1)	Probably under-parametrized
FRCC	ARMA(p,q)/AR(1)	Unclear results
MRO	ARMA(0,0) = White noise	
TRE	AR(1)	

3.5 Parameter Estimation

The parameter estimations serve two purposes. First, by comparing the results of the estimations for a group of neighbour models across several regions of data, it is possible to conclude on the values for p and q based on which model generally presents the strongest parameters in the estimations. Second, it simultaneously provides the final parameter estimators once the model identification has been made.

The parameter estimations for the AR(1) and four of its neighbour models, the MA(1), AR(2), MA(2) and ARMA(1,1), are presented in Table 4 in Appendix B. Due to the principle of parsimony[15] and the previously mentioned problem of few observations we only consider models up to 3 parameters (including the constant variance), as the number of observations are unlikely to support more than that.

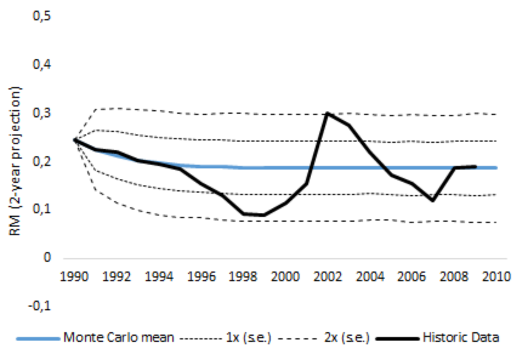
From the results it is clear that the AR(2), MA(2) and the ARMA(1,1)-models have insignificant parameters for several of the regions. Insignificant parameters are indications that the proposed model is over-parametrized, though in this case it could simply imply that there is not enough data to support the significance of the estimated parameters. Yet, the argument for excluding these models are stronger than the one for keeping them. Of the remaining two options, the AR(1) is indicated as the best model for 3 out of the 10 regions by the AIC-parameter[16]. For two regions, the AIC indicates that the MA(1) is the preferred model. Although this is only a slight advantage to to the AR(1), I choose the AR(1) representation as the final model for the underlying RM process, as this also corresponds to the results from the ACF-PACF-test and the intuition of the forces driving the process[17]. Analyses on the AR(1) fit also show no significant autocorrelation in the residuals, which indicates that the model is not under-parametrized.

The final estimators for an AR(1) representation of the projected reserve margin processes are thus given by Table 4 in Appendix B. These parameters are all within the range of stationarity[18], thus avoiding the problem of unit-root.

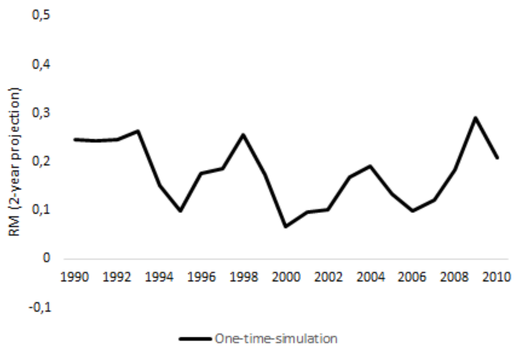
[15]"The simplest of two competing theories is to be preferred". Fundamental principle in time series analysis.
[16]The Akaike information criterion (AIC) is a measure of the relative quality of several statistical models for the same set of data, and considers both the likelihood and number of parameters of the models.
[17]The AR(1) is the discrete equivalent to the classical Ohlstein-Uhlenbeck Mean-Reversion model.
[18]For an AR(1) model, this is given by $|\phi_1| < 1$.

3.6 Model Evaluation by Simulation

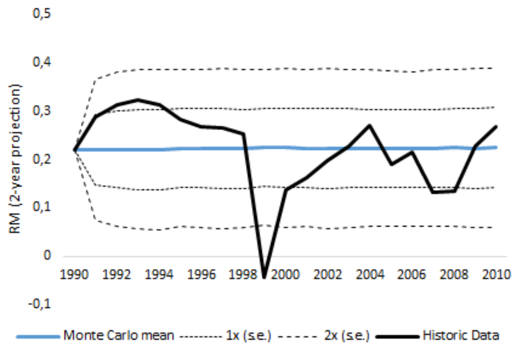
The appropriateness of the proposed model for the RM data is validated through evaluating the simulation properties of the model. Figure 4 shows the probability distributions (mean, 1x s.e. and 2x s.e.) for each of the three regions of interest PJM, NYISO and NEISO. These distributions are found by Monte Carlo simulation and they clearly show that in the long term, the AR(1) representation of the RM quickly tends towards a near-to-constant mean. Only one historical year-observation falls outside two standard deviations from these means, which is the extremely low projection for NYISO in 1999. Since the RM really shouldn't experience negative values, it is reasonable to consider this event as a deviation from the underlying process. The mean levels from the plots corresponds with the mean-parameters from Section 3.5, where PJM has a mean of 18.7%, NYISO a mean of 22.3% and NEISO a mean of 19.7%. These results seem reasonable, and are all above the "minimum rate" (the NERC Target rate) of 15%.



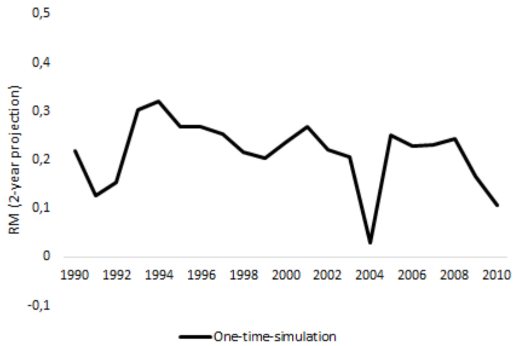
(a) PJM: Monte Carlo distributions



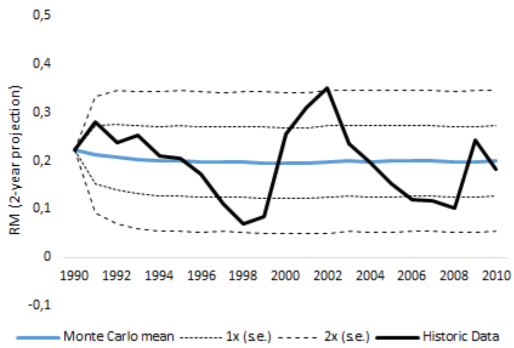
(b) PJM: One-time simulation



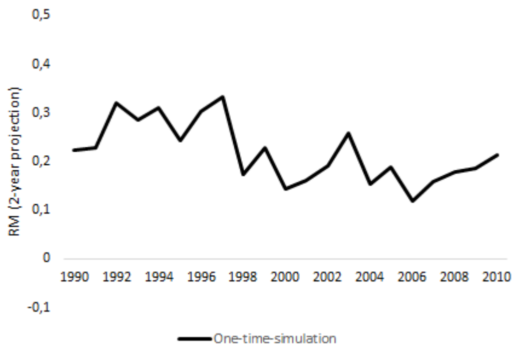
(c) NYISO: Monte Carlo distributions



(d) NYISO: One-time simulation



(e) NEISO: Monte Carlo distributions



(f) NEISO: One-time simulation

Figure 4: Distributions and Simulations for Projected Reserve Margin
Figures (a), (c) and (e) illustrate historical values for the projected reserve margin for the regions PJM, NYISO and NEISO together with its expected distribution (mean, 1x and 2x standard errors) for each year in the period 1991-2010 with the historical value from 1990 as the initial condition. The expected distributions are found by Monte Carlo simulations. Figures (b), (d) and (f) illustrates examples of single simulations for the same regions and time period. The plots show that the historical values are for the most part well within their expected distributions, and the one-time simulations appear to correspond well to the historical values.

In addition, simple one-time simulations of the models are shown in Figures 4b, 4d and 4f. These plots indicate that the main characteristics from the historic data has been maintained in the model representation, supporting the fitness of the AR(1) model.

3.7 Intuitive Interpretation of the Results

I have previously described how both the actions of the plant managers and the grid operators cause mean-reverting effects; plants entering and leaving the operating state based on the market price (proxied by the RM) and grid operators intention to maintaining a safe reserve margin level yet not wasting resources in unused capacity. In descriptive terms, these stakeholders are performing actions as "responses" to the RM they observe, which in turn affect the future RM thus creating the mean-reverting effect. An important distinction, however, is that the responses made by different stakeholders can have consequences that persists at different lengths of time into the future. This is in parallel to the different timeframe these stakeholders consider when evaluating investment decisions. This distinction is described in the following examples.

Existing peak plants respond to the RM by exercising switching options. When peak plants are considering shutdown or startup options, their considerations extend into the relative short term future. The consequences of exercising these options have a direct impact on the RM in the short term, or equivalently in the following period $t + 1$ as described in the simplified timeline in Figure 2 in Section 2.2. By the time of the second period $t + 2$ the peak plant could have exercised new options, thus limiting the impact of the response made from the first period t. This suggests that existing peak plants carry a *short term mean-reverting* effect on the RM. Note that even though peak plants sometimes are evaluating the RM for longer time horizons, this is often more related to the considerations of exercising an abandonment option. Entering the retirement state does not contribute to the mean-reverting effect, however, as it would never be profitable to abandon a plant whilst in the operating state (Fleten et al., 2014). Abandonment will thus only occur from the mothballing state where the capacity of the plant is already not included in the RM, thus preventing this response by the peak plant to contribute to the mean-reverting effect.

Base load plants produce more or less continuously in order to deliver the minimum demanded amount of electricity to the market. Although the reserve margin is defined for peak demand, it is reasonable to assume that the low projected reserve margins also signals that the market is profitable for base load plants, for instance if a change in peak demand is due to a general increase in electricity consumption due to an economic boom. Thus the projected reserve margin could affect decisions to construct or abandon base load plants, which definitely affects the RM which is defined based on total capacity. However, this mutual effect is distinguishable from the effects between the RM and the peak plants. Whereas peak plants consider the near future for their investment decisions, base plants must assess the if the long-term price level is sufficient to justify the investment. Likewise, the construction or abandonment of a base plant will (ceteris paribus) cause a long-term effect on the RM. Thus, this suggests that base load plants carry a *long term mean-reverting* effect on the projected reserve margin. Note that this also the case for both planned base and peak plants. The decision(s) to initiate or continue their construction are certainly dependent on the projected reserve margins on a longer timeframe than what is considered for startup and shutdown options, and once completed, their existence will effectively rise the long-term capacity in the market.

The grid operators are in turn capable of exerting a mean-reverting effect on the RM both in the relative short-term and long-term. From a reliability point of view, they have two mandates; exerting direct control when system failure is imminent and maintaining the system balance over the long-term so that such critical incidents do not happen. Through their means of executive actions and market influence through the capacity market, the grid operators clearly have the capability of influencing the RM over various points in time.

Based on these considerations, it seems logical that the projected reserve margin should exhibit characteristics more complicated than what is given by the three parameters of an AR(1) representation. A representation which includes short-term and long-term characteristics seems intuitively reasonable. Realistically, however, this is probably more relevant for a continuous representation of the RM and not the annual process that I am analyzing in this paper.

In order to conclude on the appropriateness of the AR(1) as a representation for the annual RM process, a relevant question is arises: how long is the "long-term" timeframe discussed above? A crude indicator for this can be found in the projected total capacity data from the ES&D database. When comparing all annual ten-year projections over the sample period, I found that while the projections vary significantly over the first 3-4 or so years, they essentially become identical on a longer horizon. This suggests that the plants have relatively specific plans for up to 3-4 years into the future, but only have general continuations of those plans for the years beyond that. The AR(1) model is fully capable of carrying on information from the process four lags back[19], which would then cover the most relevant time period in which the RM process is likely to exhibit mean reverting characteristics.

In light of this discussion, I conclude that the AR(1) model is a simple but fairly intuitive representation of the annual RM, which also is supported by the data.

[19]There are two types of memories associated with an autoregressive model. The most explicit is related to the lag length, and can be referred to as a process' *direct* memory of its past like in the way an AR(2) model is directly influenced by the value two years in the past. In contrast, the second type is an *implicit* memory of past lags which is carried on by more recent lags. An AR(1) model remembers one year back to a lag which also remembers one year back, going back to infinity. The strength of the memory is indicated by the AR-coefficients, which for the RM data are relatively strong (mean of 0.66 in a range from 0.43 to 0.81).

4 Regulatory Uncertainty

The following section contains an independent time series analysis of the driver regulatory uncertainty. The section first analyse the data on the basis of standard modelling techniques. In the later part, I repeat the analysis when including a quantified representation of the concept of diffusion, which yields a better result.

4.1 Visually examining the data

As I explained in Section 2.5, I utilize the regulatory uncertainty variable REGUNCERT defined by Fleten et al. (2012) and later extended by Kaldahl and Ingebrigtsen (2014). The final data set displaying the presence of regulatory uncertainty for all 48 mainland U.S. states in the period 1990-2011 is reproduced from Kaldahl and Ingebrigtsen (2014) below.

Table 3: Historic Data for Regulatory Uncertainty
Data illustrating the presence of regulatory uncertainty in 48 U.S. states from 1990 to 2011 as defined by Kaldahl and Ingebrigtsen (2014). Their proxy variable for regulatory uncertainty, REGUNCERT, equals 1 (black background) if a U.S. state experience regulatory uncertainty in a given year, or 0 (white background) if the U.S. state does not.

State	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
AZ	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
AR	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
ID	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
IL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IN	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IA	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
ME	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
MA	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
MS	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
MO	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
NE	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
NV	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
NH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NJ	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NM	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
NY	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
NC	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ND	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
VT	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
VA	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
WV	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
WY	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The data is thus consisting of 48 individual time series of the REGUNCERT-process, which by definition is discrete in time and space and takes the value REGUNCERT = 1 if regulatory uncertainty is present for a given year in a U.S. state and REGUNCERT = 0 if not. From Table 3 I make the following general observations of the behaviour of this process.

Firstly, the data indicates that the process for the majority of the time is in a state of no regulatory uncertainty over this sample period. This fits with intuition, as regulatory uncertainty is an indicator of deregulation policy being on the political agenda in a U.S. state while still not concluded upon or implemented yet. Such unresolved political topics don't remain on the agenda forever, but is rather present for finite and continuous periods of time.

This latter point is also supported by the observed data, as it shows periods of regulatory uncertainty occurring (for the most part) in consecutive periods with relatively few transitions from one state of uncertainty to the other. This suggests that the process is highly persistent, meaning the process tends to remain in its current state rather than changing.

Additionally, the data demonstrate some examples of periods of regulatory uncertainty occurring several separate times during the sample period. The evidence of this characteristics, though occurring infrequently, is supported by intuition as it is possible to go backwards on the Retail Competition Index from Table 1. Basically, some U.S. states have experienced having deregulation on the political agenda for some time, then abandoned or finished with it, before it reappeared another time. This feature appears two times in the data, for the U.S. states Delaware and Maryland. The majority of the U.S. states thus only experience one (35 U.S. states) or none (11 U.S. states) consecutive periods of regulatory uncertainty.

Finally, a telling characteristic of the REGUNCERT-process is the appearance of clustering of regulatory uncertainty in certain years. Particularly, from the mid 1990s to the early 2000s, the majority of all U.S. states experienced a state of regulatory uncertainty in retail competition. This suggests that the individual REGUNCERT-processes for U.S. states are somewhat correlated in time.

4.2 Choice of Model

Like with the projected reserve margin, I will assume that the regulatory uncertainty processes for all 48 U.S. states follow the same stochastic model, but are distinguishable in their individual parameter values.

The fact that the REGUNCERT-process is discrete in time and space excludes any representation from the popular ARIMA-classes of time series models which operate in continuous space. However, two potential model that can fit the data are the Markov Chain and the Poisson representation. Whereas the Markov Chain is fully described with constant probabilities for every possible transition in the state space, the Poisson representation is based on probability rates for certain events (i.e. transitions) to occur. For this simple case of a state space of only two dimensions, both these models can be defined by only two parameters[20] which makes them equivalent in terms of the amount of information that can support each parameter. Since the two model classes don't allow for a simple quantitative comparison like the ACF-PACF-test for the neighbourhood ARMA-models, the selection of an appropriate model in this case must be made on more qualitative arguments.

I choose to fit the REGUNCERT data to a Markov Chain as this representation assumes that the state of regulatory uncertainty for a coming period is dependent on the state of the current

[20]Poisson process: two probability rates, one defining the occurrence of a transition from a state of regulatory uncertainty to a state of no regulatory uncertainty, and another for the reverse event. Markov Chain: a transition probability matrix with four parameters, which reduces to two parameters under the restriction that requires all parameters in each row to sum to 1.

period[21]. I find this a reasonable assumption for the REGUNCERT-process, as it is mainly defined on the basis of the Retail Competition Index. That is, I find it logical that if a political process of deregulation has been initiated but not completed in period t, then the probability of the same being the case for period $t+1$ should be clearly different compared to if the process had never begun or been completed in period t. Furthermore, even though the Markov Chain by definition assumes the probability distribution (transition probabilities) to be constant over time, I find it easier to adapt the Markov Chain representation to accommodate for clustering than with a Poisson representation.

The following analysis I first estimate and evaluate the parameters of a standard Markov Chain representation, which is incapable of capturing clustering, before proposing an extension to the Markov Chain by treating the transition probabilities as time-variant in Section 4.5.

4.3 Parameter Estimation and Adaptation

A standard Markov Chain is fully defined by its transition probabilities (Norris, 1998). For the REGUNCERT-process, which has a state space of two dimensions, its Markov Chain representation can be defined by two independent probabilities, as seen in Figure 5. These are

- ρ_{01}, the probability that the next state will be REGUNCERT $= 1$ given that the current state is REGUNCERT $= 0$, and
- ρ_{11}, the probability that the next state will be REGUNCERT $= 1$ given that the current state is REGUNCERT $= 1$

If considered in the framework that the presence of regulatory uncertainty is the result of an ongoing political process of implementing deregulation policies, ρ_{01} can be viewed as the probability of such a process to be *initiated* in the first place, whereas ρ_{11} represents the *persistence* of the process, or how long time it will take for the process to be completed in the legislative arena. These two interpretations will be examined more closely in Section 4.5.

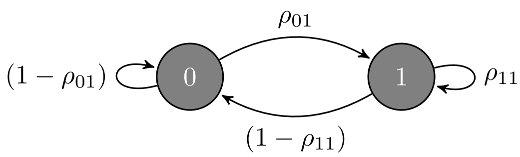


Figure 5: State Diagram for the Markov Chain Representation of Regulatory Uncertainty
When represented as a Markov Chain, a REGUNCERT-process is fully defined by ρ_{01}, the probability of *initiating* regulatory uncertainty if no currently exists, and ρ_{11}, the probabilistic *persistence* of staying in a state of regulatory uncertainty once in it.

It can be shown that the estimators for the transitions probabilities in a positive regular Markov Chain is given by[22]

$$\hat{\rho_{01}} = \frac{n_{01}}{n_0} \qquad\qquad \hat{\rho_{11}} = \frac{n_{11}}{n_1} \tag{2}$$

where n_{ij} is the number of observed transitions from state i to state j and n_i is the total number of observed transitions from state i. These formulas do assume a large number of available

[21] This is known as the Markov property.
[22] Bhat (1960) derive these equations using maximum likelihood.

observations, an assumption which is weak in the case of the REGUNCERT-process with only 21 observations. Still, it is possible to apply these formulas to retrieve reasonable guesses for the transition probabilities, which can be qualitatively improved when necessary.

Applying equations 2 to the 48 time series for the regulatory uncertainty yields estimators values for the ρ_{01} between 0.0% and 15.4% and ρ_{11} between 0.0% and 90.0%. Naturally, the 0% probabilities occur when no such transitions have occurred during the sample period. Excluding these these cases, ρ_{01} ranges from 5.0% and 15.4% and ρ_{11} between 50.0% and 90.0%. Although crude numbers, the estimates correspond with the intuition from the data that the probability of initiating a deregulation process should be low, while the persistence of remaining in a state of regulatory uncertainty is much higher.

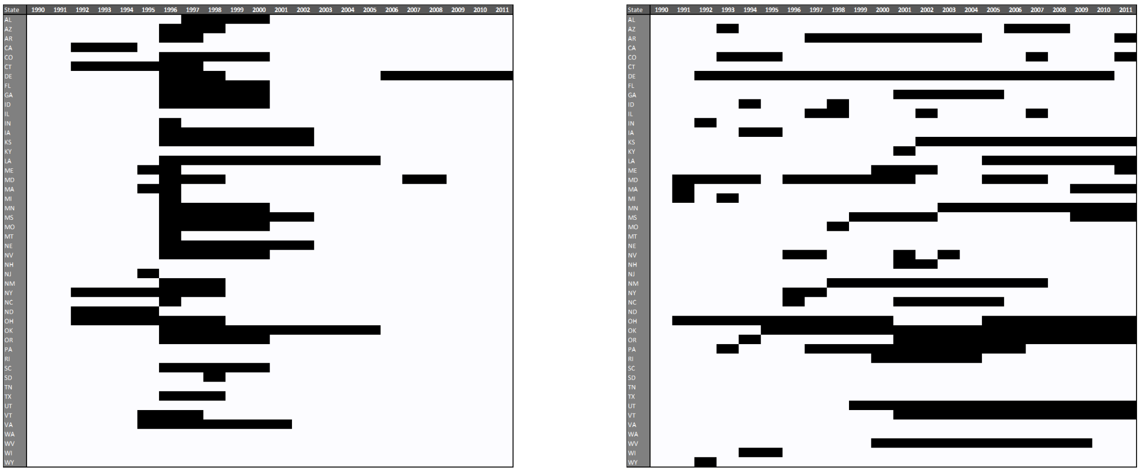
However, estimates are missing for ρ_{11} for the 11 time series that have experienced no regulatory uncertainty. Additionally, some of the estimators for ρ_{11} are at 0%, which is obviously unrealistic and only occurs because there are few observations available. I make the argument that every U.S. state has non-zero probabilities for experiencing regulatory uncertainty, even for U.S. states that might already have implemented deregulation since such policies could be "undone". Thus, all four transitions illustrated in Figure 5 should be positive non-zero, forcing $0\% < \rho_{01}, \rho_{11} < 100\%$.

For that reason, I implement the following three qualitative adaptations to the estimator results. 1.) When a U.S. state has experienced no regulatory uncertainty, it is impossible to deduce an appropriate value for the estimator of ρ_{11} based on the data for that U.S. state alone. Thus, a logical approach is to assign it the expected value of *any* U.S. state; that being the average of all (non-zero) estimator values amongst the other 48 U.S. states, which is 76.3%. 2.) When a U.S. state has experienced regulatory uncertainty but still gets an estimator for ρ_{11} equal to 0%, this is because there has been only one observation of regulatory uncertainty in that state and that was not followed by another. Thus there is some information about the parameter value available. It is insufficient for a proper estimate but does indicate that the proper value should be lower than the same parameter in other U.S. states. Thus, I assign this estimator the halfway point between 0% and the lowest (non-zero) estimator found for ρ_{11} in other U.S. states which is 50%, which makes the halfway point at 25%. 3.) Finally, using identical logic, I assign the halfway point between 0% and the lowest observed value elsewhere for ρ_{01} (5%) for any U.S. state not having observed regulatory uncertainty, which is 2.5%. The final estimators for all 48 U.S. states are summarized in Table 5 in Appendix C.

4.4 Model Evaluation by Simulation

Examples of a one-time simulation[23] of the standard Markov Chain representation of regulatory uncertainty for all 48 U.S. states are illustrated in Figure 6 together with the original data. It is clear from the plots that the reduced form representation manages to replicate some of the features of the observed data, like the occurrence of multiple consecutive periods of regulatory uncertainty for a single U.S. state. However, the simulated values are distributed more evenly over the whole sample period.

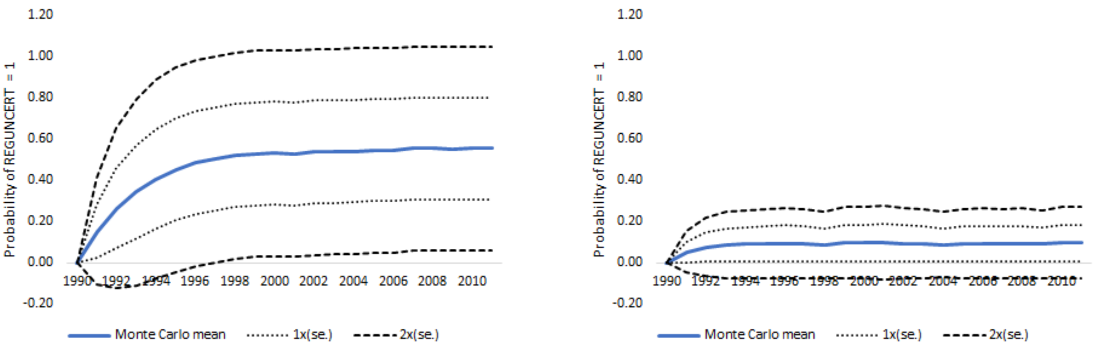
[23] Simulations are performed using the Inverse Transform Method (Ross, 2007).



(a) Historic data   **(b)** One-time-simulation, Markov Chain

Figure 6: Evaluation of Standard Markov Chain Representation
A comparison of the observed values for the regulatory uncertainty in (a) with simulated results for the same U.S. states and period 1990-2011 in (b). The plots show that the simulated Markov Chain manages to replicate many features of the original data, apart from the clustering in the mid-to-late 1990s.

In fact, Monte Carlo simulations show that the probability of a U.S. state experiencing regulatory uncertainty for a given year quickly stabilizes at a near-to-constant level, as illustrated in Figure 7. This is a clear indicator that a standard Markov Chain does not capture the time-varying characteristics observed in the data.



(a) Delaware, $\rho_{01} = 15.4\%,,\rho_{11} = 87.5\%,$ **(b)** Maine, $\rho_{01} = 5.3\%,\rho_{11} = 50.0\%$

Figure 7: Monte Carlo Distributions of Probability for Regulatory Uncertainty
Probability distributions for how likely a given year is to experience regulatory uncertainty for the two U.S. states (a) Delaware and (b) Maine. REGUNCERT = 0 in 1990 serves as the initial condition. For both cases, the probability quickly reach near-to-constant levels, indicating that the model does not capture clustering in time. The plots illustrate a drastic effect on the probability distribution for high (a) and low (b) parameter values.

I find this lacking characteristic problematic in the setting of analyzing switching in peak power plants. Therefore, in the following subsection I reformulate the Markov Chain with time-varying parameters.

4.5 Time-Varying Probabilities by Policy Diffusion

The feature showing how regulatory uncertainty tends to occur simultaneously in many U.S. states for certain years suggests that the the regulatory uncertainty processes amongst U.S. states do not occur independently of each other.

This observation is collaborated by Andrews (2000), who specifically examines the regulatory reforms of the U.S. electricity sector from 1993 to 1999. He claims that "states rarely adopt new policies in isolation, but rather as part of a national system of emulation and competition". His argument is that "innovative legislatures serve bigger, richer, more urbanized, more heterogeneous states, with neighboring states looking to these regional leaders while keeping pace with their less innovative peers". Essentially, as some states starts to implement new innovative legislation, the "trend will continue" amongst other fellow states. Andrews describe this as the diffusion of new policy innovations.

I intend to quantify this concept in order to replicate the time-varying effect seen in the data. This requires some assumptions as to which parameter or parameters in the Markov Chain representation that are likely to be linked across states. In section 4.4, I described ρ_{01} as the probability of initiating a deregulation process and ρ_{11} as an indicator of the persistence (or "length") of that process. I make the assumption that the persistence of a deregulation process is primarily dependent on the internal political conditions of an individual U.S. state. As restructuring policies are set by the individual State Senates, the lead time of such policy processes should vary depending on the particular Senate's composition of senators and their party affiliations, their personal political convictions and connections to interest groups, as well as the specifics of the local politics of that state. The initiation of such a policy process, however, is arguably more susceptible to the general popularity of the policy in other states. Therefore, I make the simplified assumption that the ρ_{11} are independent state-specific parameters which remain time-invariant, whilst the ρ_{01}, although still state-specific, are dependent on the general popularity of the policy across U.S. states.

Hence, I refer to the *diffusion effect* as the increase or decrease of ρ_{01} depending on whether or not the policy is "popular" in a particular year. I define a policy to be popular if there are more U.S. states currently experiencing regulatory uncertainty than on average, and unpopular if there are less than average[24].

I quantify this effect by the *diffusion factor*, defined as the difference between the fraction of all U.S. states experiencing regulatory uncertainty in a given year (referred to as the *National Uncertainty Fraction*) and the mean of this fraction over the sample period. Thus, the diffusion factor for year t is given by

$$DF_t = F_t - \mu_F \tag{3}$$

where F_t is the National Uncertainty Fraction in year t and μ_F is the mean of F_t over the sample period. These concepts are illustrated in Figure 8. As seen from the figure, the diffusion factor is positive when regulatory uncertainty occur in more states than on average and negative if not, as seen in the years 1998 and 2006 respectively.

[24]Note that I indirectly assume that the presence of regulatory uncertainty as defined by Kaldahl and Ingebrigtsen (2014) is equivalent with an ongoing deregulation process in a particular state. This is not entirely correct as their variable isn't only dependent on the Retail Competition Index, but it serves as a sufficient proxy in this case.

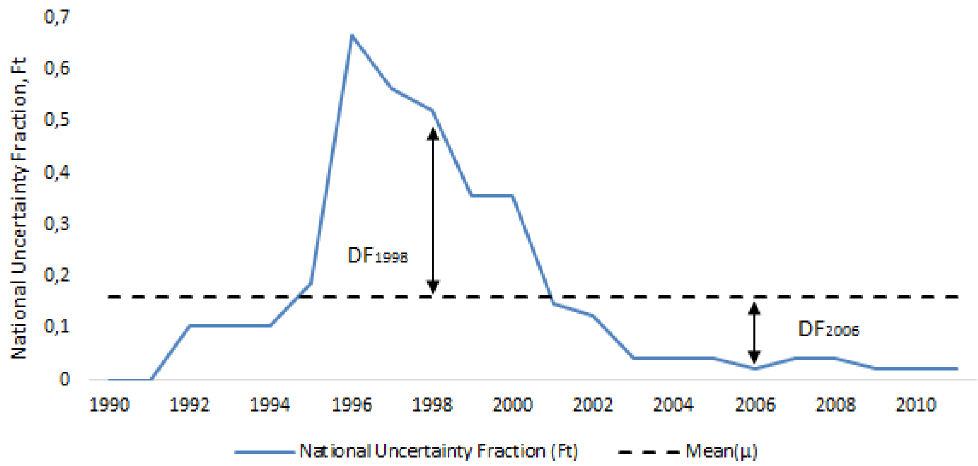


Figure 8: National Uncertainty Fraction and the Diffusion Factor
The figure shows the proportion of all U.S. states having REGUNCERT = 1 in a given year (National Uncertainty Fraction) and its expected value (mean) for every year in the period 1990-2010. The National Uncertainty Fraction is a distribution over time serving as a proxy for the probability distribution of when a U.S state is experiencing regulatory uncertainty. Its mean is thus a proxy for the probability of any U.S. state experiencing regulatory uncertainty in any year. Together they form the diffusion factor, which increases the probability of a U.S. state entering a new state of regulatory uncertainty if deregulation policy is "popular" that year, or reduces it if it is not.

Next, I define the *degree of diffusion* as a scaling factor of how susceptible a particular U.S. state is to be influenced by the popularity of a particular policy. It is likely that due to e.g. local culture and traditions the diffusion effect in a U.S. state might be stronger on a certain policy area than for others. For example, it is conceivable that a conservative state like Texas is less likely to be influenced by an eventual trend of increased gun legislation than a liberal state like Massachusetts. They would thus have different degrees of diffusion in this policy area.

Definition: Diffusion model. The aforementioned concepts are summarized in the following expression for the *dynamic* version of the transition probability ρ_{01},

$$\rho_{01,t} = max[\underline{\rho}, min[\overline{\rho}, \rho_{01}(1 + K \times DF_t)]] \tag{4}$$

where ρ_{01} is the long-term average transition probability given by equation 2, DF_t is the diffusion factor in year t and K is the degree of diffusion for a given U.S. state, and $\underline{\rho}$ and $\overline{\rho}$ are the minimum and maximum values respectively of the transition probability ρ_{01}. The restriction $\underline{\rho} \leq \rho_{01,t}, \rho_{01} \leq \overline{\rho}$ applies for all t.

Note that the diffusion model reduces to the standard Markov Chain model used in Sections 4.3 and 4.4 if $K = 0$[25]. That is, if the susceptibility of U.S. state to be influenced by the time-varying popularity of a particular policy is zero, then the transition probability is time-invariant.

The appropriateness of this model is demonstrated in Figure 9, which depicts the Monte Carlo probability distributions for all 48 U.S. states over the sample period for varying degrees of diffusion. To best demonstrate the qualities of the diffusion model in this example, all U.S. states are assumed to have the same value for K. The figure clearly shows that the probability distribution for REGUNCERT becoming increasingly time-variant with higher values of K. The extreme case of $K = \infty$ demonstrate a clear higher probability for regulatory uncertainty to occur for all U.S. states in the mid-to-late 1990s, a pattern which fits well with the historical values. An interesting

[25]It is assumed that $\underline{\rho} \leq \rho_{01} \leq \overline{\rho}$ always holds.

feature is shown for the other extreme case of $K = -\infty$, where the probability distribution is inverted. Going back to the gun legislation example, it is conceivable that for particular issues with highly polarized public opinions like gun legislation[26], increased national popularity of a policy might actually increase public opinion *against* that policy in a particular state, thus creating an opposite diffusion effect.

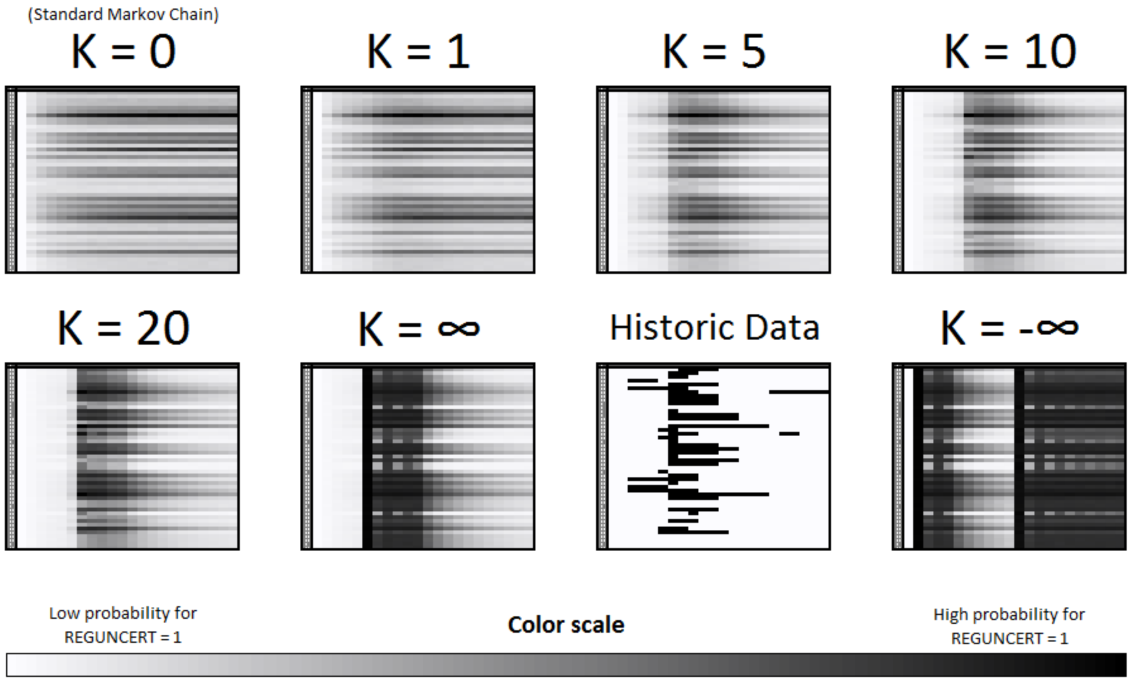
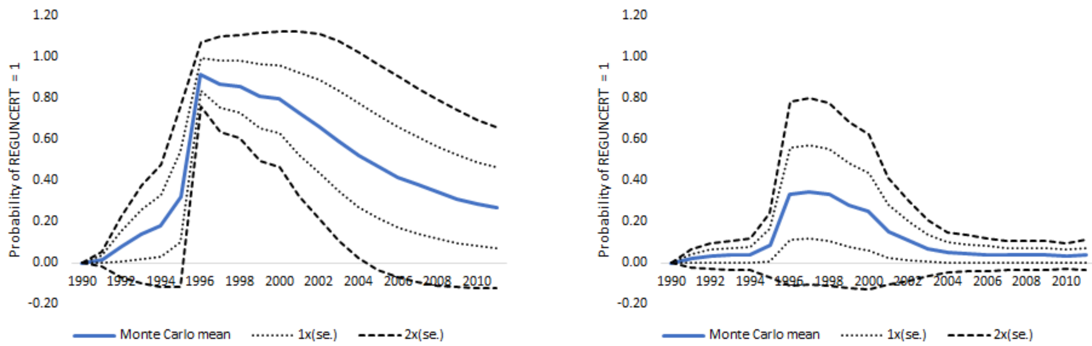


Figure 9: Probability Distributions of REGUNCERT for Varying Ks
Probability distributions for how likely it is for any of the 48 U.S. states to experience regulatory uncertainty between 1991 and 2011 when REGUNCERT is represented using the diffusion model for varying degrees of diffusion. REGUNCERT = 0 in 1990 serves as the initial condition. $\underline{\rho} = 0.02$ and $\overline{\rho} = 0.98$. The plots clearly shows how the probability of experiencing regulatory uncertainty clusters in certain years, as opposed to the standard Markov Chain representation (when $K = 0$).

The time-varying qualities of the diffusion model is further demonstrated in the probability distributions for regulatory uncertainty for the individual U.S. states Delaware and Maine in Figure 10, which are given for a diffusion factor of $K = 10$. These distributions stand in clear contrast to the time-invariant distributions to the distributions from Figure 7 in Section 4.4.

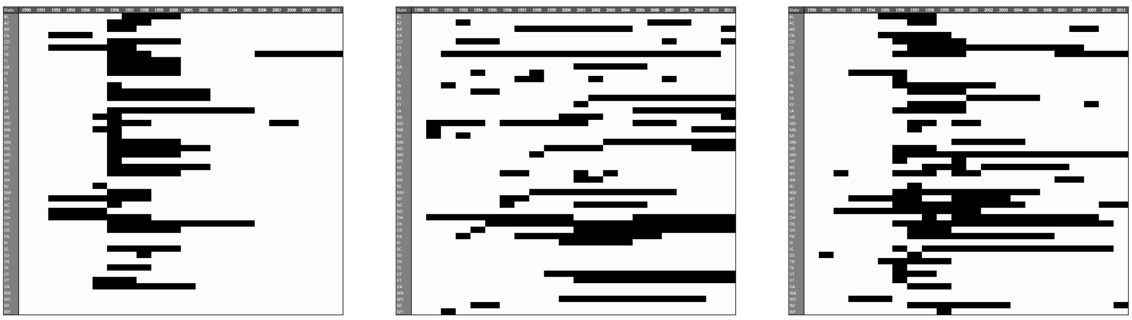
[26]Kopel (2012).



(a) Delaware, $\rho_{01} = 15.4\%,,\rho_{11} = 87.5\%,$ **(b)** Maine, $\rho_{01} = 5.3\%,\rho_{11} = 50.0\%$

Figure 10: Time-Varying Probability Distributions for Regulatory Uncertainty
Probability distributions for how likely it is that the states (a) Delaware and (b) Maine will experience regulatory uncertainty in a given year, when REGUNCERT is represented with the diffusion model, where $K = 10$, $\underline{\rho} = 0.02$ and $\overline{\rho} = 0.98$. REGUNCERT = 0 in 1990 serves as the initial condition. For both states, the probability is clearly at its highest in the mid-to-late 1990s.

Finally, the diffusion model demonstrate a clear advantage in how it captures the clustering present in the historical data over the standard Markov Chain representation, when used to simulate single realisations of the REGUNCERT-processes for all 48 U.S. states as shown in Figure 11.



(a) Historic data **(b)** One-time-simulation, K=0 **(c)** One-time-simulation, K=10

Figure 11: One-Time-Simulations for Regulatory Uncertainty
Comparison of the (a) historical data for regulatory uncertainty with simulated values through the representation of the (b) standard Markov Chain and (c) the diffusion model with parameters $K = 10$, $\underline{\rho} = 0.02$ and $\overline{\rho} = 0.98$. The diffusion model shows a clear advantage in capturing the time-variable characteristics of the original data.

Nevertheless, there are some limitations to this proposed diffusion model. Firstly, it is assumed that the National Uncertainty Fraction-distribution is known before running any simulations. Thus, the model cannot simulate the future when this information isn't available, or even outside the sample period from 1990-2010. It is plausible, however, that with research one can identify some general distribution for the National Uncertainty Fraction for which new policy innovations are implemented, which could serve as a proxy for such case. Secondly, the model doesn't distinguish between which U.S. states are leading and which are following in the innovation development. Basically, it doesn't include any time lag between when a U.S. state observes others implementing policies to when its own probability of doing the same increases. Since the model assumes annual time periods, however, this assumption is not entirely unreasonable. Thirdly, a more realistic model would allow for the popularity peak to vary in time. This could perhaps be accomplished by modelling the NUF-distribution stochastically.

All the same, despite these shortcoming I find the results from the diffusion model helpful for the analysis of the switching problem.

5 Relationship between Drivers

The drivers have so far been analysed independently from each other. This section contains a discussion on how regulatory uncertainty and the projected reserve margin influence each other.

5.1 RM influencing REGUNCERT

The push for the introduction of retail competition in the U.S. power markets was primarily driven by regional differences in retail electricity prices. As such, retail electricity prices functions as a driver for regulatory uncertainty. The reserve margin respond to market conditions in the wholesale market and is thus an indicator of wholesale prices. Since there is no unambiguous relationship between retail and wholesale electricity prices, there is little intuition in support of the reserve margin driving regulatory uncertainty.

Additionally, the data for the REGUNCERT variable from Kaldahl and Ingebrigtsen (2014) was specifically filtered for effects of high and low retail electricity prices, thus making the RM a driver for REGUNCERT even less likely.

This is not to say that the projected reserve margin is not capable of spurring other forms of regulatory change. For instance, consistently low reserve margins would be of reliability concerns and could lead policy makers and regulators to push for e.g. legislation requiring all households to install smart meters in order to encourage dynamic demand and enabling demand response mechanisms. However, in the interest of evaluating the relationship between the drivers for switching as defined in this paper, this is less relevant.

5.2 REGUNCERT influencing RM

As the implementation of retail competition was intended to reduce the electricity price for consumers, it appears to have the ability to affect peak demand. However, regulatory uncertainty takes place before the deregulation is implemented and should thus not have a direct influence on peak demand. Also, Taber et al. (2005) investigates to which extent deregulation actually has succeeded in this goal of reducing retail prices and concludes that even though "most customers in deregulated states saw declines in the real price of electricity, they faced higher prices relative to customers in still-regulated states", which negates the original intention of the policy. This is additional evidence that strongly suggests that regulatory uncertainty does not affect peak demand. Thus, it is likely that for regulatory uncertainty to affect the reserve margin it must be through total capacity.

It has been shown by Fleten et al. (2012) that regulatory uncertainty related to retail deregulation has a strong influence on peak power switching decisions. Specifically, they find that the presence of regulatory uncertainty severely reduces the probability of plants shutting down from the operating state and severely reduces the probability of plants starting up from the mothballing state. Thus, regulatory uncertainty exerts asymmetrical effects on capacity. Very few peak plants are going to increase capacity by switching to the operating state but at the same time fvery few plants are doing the opposite. The net effect of peak plants postponing their switching decisions is that the total capacity represented by peak plants remain the same. That means that regulatory uncertainty has a negligible effect on projected reserve margin through existing peak power plants.

Billingsley and Ullrich (2011) investigates the effect of regulatory uncertainty on *planned* future investments in capacity. This refers to the construction of new power plants or expansions of existing ones. They find that regulatory uncertainty in the 1990s had a massive depressive effect on firms investing in new capacity and that this development was mirrored with a correspondingly significant rise in investments once much of the uncertainty dissolved in the early 2000s. As opposed to the scenario with the existing peak power plants, this represents a unidirectional effect on capacity at any given time. The presence of regulatory uncertainty should decrease total capacity along with the projected reserve margin.

I an attempt to test this relationship I modeled the RM as an AR(1) model with REGUNCERT as an explanatory variable for the ten NERC regions[27]. This gave very conflicting results. For only two regions were the REGUNCERT coefficient significant at the 95% confidence interval. Even more surprisingly were the results indicating that four of the regions had *positive* REGUNCERT coefficients, indicating that reserve margin should *increase* during regulatory uncertainty which contradicts the aforementioned intuition and literature.

I try to explain these results by taking a closer look at the hypothesis of Billingsley and Ullrich (2011). The historical values for the projected reserve margin in Figure 3a in Section 3.3 and for the regulatory uncertainty in Table 3 in Section 4.1 support their theory. The RM sank drastically under the time dominated by regulatory uncertainty in the 1990s and then increased dramatically when regulatory uncertainty dissipated in the period 2000-2003. This observation might prompt a rash conclusion. Are the time series for RM and REGUNCERT simply negatively correlated at all times? I argue that the relationship is not as simplistic. I find it reasonable that regulatory uncertainty represents a depressive force on the projected reserve margin *once it exists* (when REGUNCERT = 1) but I find it unreasonable that it should have any effect on the reserve margin when it is non-existing (when REGUNCERT = 0). The argument lies in the plot of projected reserve margins from Figure 3a. The period 2004-2009 represents a similar development as in 1990-2003, with an initial general decrease in projected reserve margin followed by a rapid increase. However, this is during a period of practically no regulatory uncertainty according to Table 3. This represents an inconsistency in how regulatory uncertainty affect reserve margin, if one assume that the increase in reserve margin from 2000-2003 was due to REGUNCERT=0. Rather, I make the distinction claiming that it was the *termination* of REGUNCERT=1, which in practicality "unleashed" firms stuck on the sideline due to the uncertainty, that fueled investments in new capacity. The regressions where REGUNCERT acted as an explanatory variable was taken over the whole sample period 1990-2010. The reason why this gives contradicting results is because it assumes that values of REGUNCERT = 0 conveys information about the behaviour of the RM, which intuitively it should not.

The implications of this perspective is that REGUNCERT cannot act as an explanatory variable for RM for the whole sample period 1990-2010, but only during the years when REGUNCERT = 1. Alternatively, any model representation with the two drivers in conjunction must account for this relationship during discrete periods of time with some kind of control variable, eliminating the "effect" of the regulatory uncertainty when REGUNCERT = 0. I do not attempt such a representation in this paper but suggest it as a topic for further research.

[27]In order to compare the projected reserve margin (region-specific) to the regulatory uncertainty (state-specific), I create a region-specific REGUNCERT proxy variable given by

$$REGUNCERT_r \equiv \frac{\sum_{s=1}^{S} \alpha_{r,s} REGUNCERT_s}{\sum_{s=1}^{S} \alpha_{r,s}}$$

where $REGUNCERT_r$ represents the regulatory uncertainty of region r, and $\alpha_{r,s}$ is the fraction of the area of state s located in region r, and S is the space with all states present in region r.

6 Conclusion

This paper provides a time series analysis of the characteristics and reduced form representations of two stochastic processes acting as drivers for switching in peak power plants. I investigate the one-year projected reserve margin and regulatory uncertainty associated with the introduction of state-level retail competition. I use data for a regulatory uncertainty proxy for 48 U.S. states from 1990 to 2011, as well as demand and capacity projections for ten NERC reliability regions in the U.S. from 1990 to 2010. The estimated parameters for the model representations of the drivers are summarized in Table 4 in Appendix B and Table 5 in Appendix C.

I find that the annual data on projected reserve margin is best described as an AR(1) model. Its mean-reverting properties fits well with intuition of the process. However, I find it likely that the underlying continuous process is more complex, potentially including both short-term and long-term mean reverting characteristics. This is, however, not possible to determined based on available data.

Regulatory uncertainty exhibits many features consistent with a standard Markov Chain model. However, I find that its data can better be explained by allowing the transition probabilities for the Markov Chain to vary over time. This resulting model demonstrate an useful ability to replicate the behaviour of the data in simulations.

To the best of my knowledge, the method I use to construct the dynamic probabilities for the Markov Chain is new to the literature. It is a simplistic quantification of diffusion - the tendency for new ideas to spread across groups. It utilize the distribution of the idea's popularity over time to update the parameters of the Markov Chain. Although developed in order to model regulatory uncertainty, the methodology should be transferable to other areas.

I find it likely that regulatory uncertainty acts as a depressing force on projected reserve margin when it exists (REGUNCERT = 1) but that it should be uncorrelated with projected reserve margin when it does not (REGUNCERT = 0). This makes it difficult to simply include regulatory uncertainty as an explanatory variable in the model for projected reserve margin. This should rather be taken under consideration in any direct applications where the two drivers are used in conjunction.

A possible use for the reduced form representations developed in this paper is in a dynamic programming model, which for instance can be used to develop appropriate decision rules for peak power switching. The reduced form representations of the drivers allow for simulation of the environment of the switching, which in turn can be used to test the appropriateness of the aforementioned decision model.

Further work should be done to improve the models. The scarce availability of data in annual form creates limitations on the potential complexity of the models. Additionally, the low number of observations reduce the reliability of the estimated parameters of the identified models. This second point can likely be remedied by the application of more advanced statistical methods which utilizes the fact that the data comes in the form of panel or cross-sectional data. Through the construction of hierarchical models and Bayesian inference, it is possible to use the collective information from all 48 U.S. states and 10 NERC regions to improve the estimations for the parameters in the individual time series. A brief explanation to this concept is included in Appendix A.

Interesting topics for further work includes an empirical survey amongst the plant managers. Valuable information of the switching problem can be obtained by asking the plant managers directly. What drivers for switching are they actually considering? How do they form expectations of these drivers? How has regulatory changes affected switching over the past two decades? Such insight could be used to better explain results from previous research on the switching problem, as well as to spur continued research in interesting directions.

Acknowledgments

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Appendix A
General

A.1 Regions under Consideration

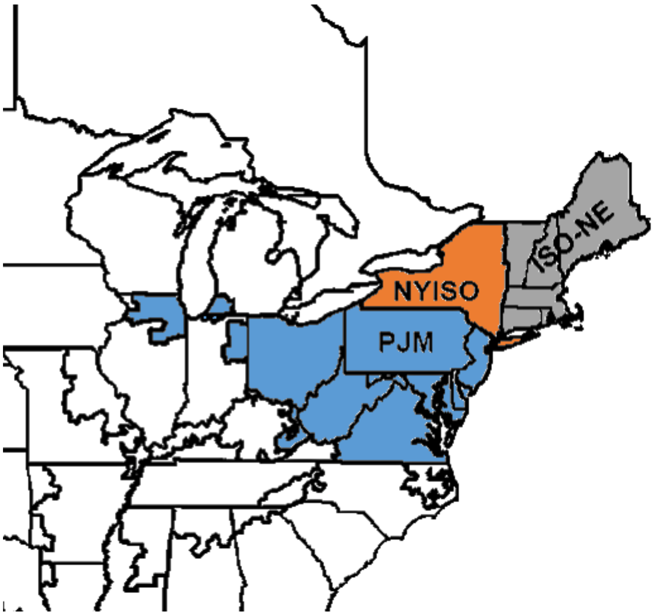


Figure 12: Regions of Interest
The three ISO-regions that are the focus of this paper. These regions corresponds sufficiently enough with the NERC-regions operating under similar names. Note: ISO-NE is also known as NEISO, which is the term used in this paper. States that are fully or partially covered by (a) PJM: Illinois, Michigan, Indiana, Ohio, Pennsylvania, West-Virginia, Kentucky, New Jersey, Delaware, Maryland, (Washington DC), (b) NYISO: New York, (c) NEISO: Maine, Vermont, New Hampshire, Massachusetts, Rhode Island, Connecticut.

Source: Adapted version of map found on FERC (2014).

A.2 Hierarchical Models and Bayesian Inference

The scarce availability of observations due to the need of annual data has been a re-occurring theme in this paper. Few observations limits the statistical foundation for even considering a great number of potential models that might well explain the data, in addition to limiting the certainty of the parameters of the simple models that can be considered. This problem limited the statistical foundation for considering higher-order models in my investigation of the projected reserve margin, left the the estimators of the regulatory uncertainty parameters with great ambiguity.

One possible solution to this problem is to take advantage of the availability of panel data. The drivers considered in this paper are in many cases a number of processes for comparable areas, regions or states, where several years of observations are available for each. I have utilized this fact a couple of purposes in this paper, i.e. for the identification of the order of the ARMA-model for the projected reserve margin and for the construction of the time-varying transition probabilities for the regulatory uncertainty processes. However, this approach can be extended and utilized further.

The approach is best described through an example. For the projected reserve margin, there exists panel data in the form of 28 time series (if one account for changes in NERC-boarders over the sample period), with 21 years of observations for each. With an assumption that all time series follows the same AR(1) model, there are three conceptual ways in how their parameters (mean, speed of reversion and random variance) can be connected across regions (Congdon, 2003):

1. They are *not*, bur rather independent from each other and dependent only on the 21 observations of their own region (this has been the assumption in this paper).
2. They are *identical*, meaning the appropriate common estimators are the average of estimated parameters across all regions.
3. They are neither independent nor identical but in some way *connected*.

The third possibility is arguably the most realistic. For example, the speed of reversion should vary somewhat across regions as the plants in different regions have different degrees of market power and are run under different managements. However, as they are presumably all exhibit profit-maximizing behaviour their responsiveness to projected reserve margins should not be completely independent of each other. Such an inter-dependency between parameters can be statistically described as a hierarchical model, in which the parameters themselves are treated as random variables and thus as individual realizations from the same distribution. By Bayesian inference, it is possible to use this relationship to "lend" information from other regions to improve the accuracy of the parameters of a single region, thus utilizing all 28×21 observations for the parameter estimation of a *single* time series.

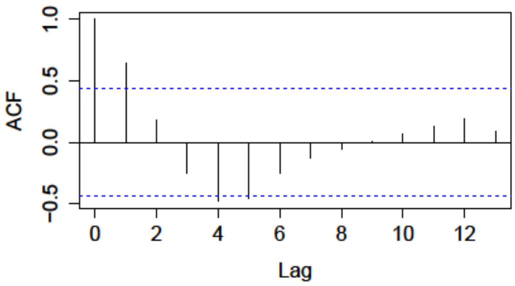
Clearly, this method is highly relevant for the analysis of this paper and should be considered a topic of further research[28].

[28] Wang and Ghosh (2004) uses the Bayesian approach to develop the Random Coefficient AutoRegressive (RCAR) model, which would be a good place to start.

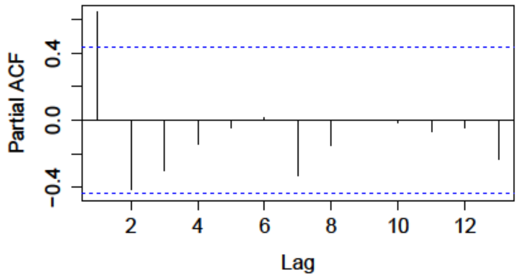
Appendix B

Reserve Margin

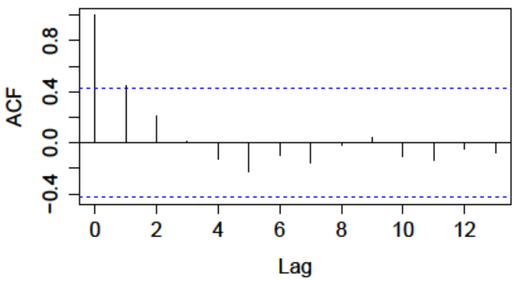
B.1 Sample ACFs and PACFs



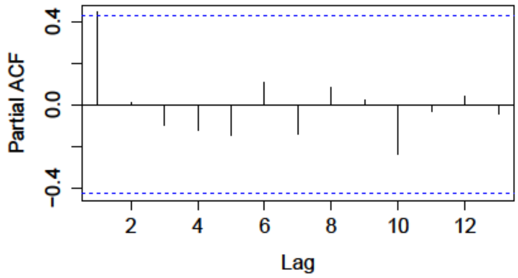
(a) PJM: ACF



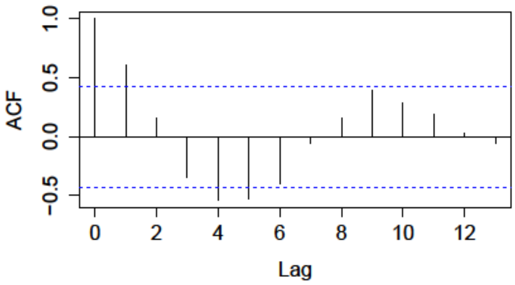
(b) PJM: PACF



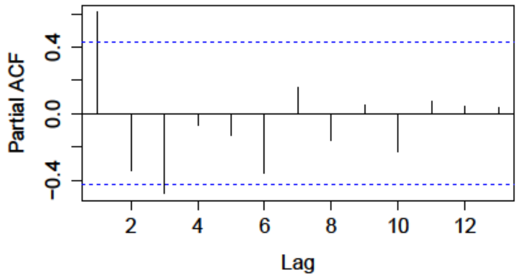
(c) NYISO: ACF



(d) NYISO: PACF



(e) NEISO: ACF



(f) NEISO: PACF

Figure 13: ACF and PACF for Projected Reserve Margin
Plots of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) for the projected reserve margins in NERC-regions PJM, NYISO and NEISO. All three combinations of plots arguably indicate that the ACF is tailing off as a damped sine wave while the PACF is cutting off after lag 1. According to Wei (2006), this is consistent with the characteristics of an AR(1) model.

B.2 Estimated Parameters

Table 4: ARIMA-regressions for Projected Reserve Margin
The table shows the projected reserve margin data for ten NERC-regions fitted to five neighbour ARIMA-models. The regressions show that the ARMA(1,1), AR(2) and MA(2) models fit the data poorly due to many insignificant parameters (marked with *). The AIC-parameter marks the best model for each region (indicated by lowest AIC-value in **bold**). The AIC ranks the ARIMA-models fit to the data with the following priority (best first): MA(2) with four regions, AR(1) with three regions, MA(1) with two regions. The generalization of all five models, the ARMA(2,2), is defined as

$$RM_t = c + \phi_1 RM_{t-1} + \phi_2 RM_{t-2} - \theta_1 a_{t-1} - \theta_2 a_{t-1} + a_t \tag{7}$$

$$a_t \sim N(0, \sigma^2) \tag{8}$$

Region	PJM	New York	New Eng.	NPCC	Central	S.East.	VACAR	FRCC	MRO	TRE
AR(1)										
ϕ1	0.659	0.431	0.588	0.579	0.805	0.784	0.627	0.813	0.790	0.523
s.e.	*0.162*	*0.190*	*0.166*	*0.179*	*0.126*	*0.158*	*0.168*	*0.149*	*0.176*	*0.192*
Mean	0.187	0.223	0.197	0.200	0.157	0.158	0.097	0.112	0.187 *	0.248
s.e.	*0.025*	*0.027*	*0.029*	*0.028*	*0.057*	*0.061*	*0.022*	*0.033*	*0.100*	*0.045*
Sigma^2	0.00172	0.00541	0.00346	0.00306	0.00331	0.00388	0.00158	0.00095	0.00905	0.01066
L.hood	35.0	24.9	29.5	29.3	29.6	28.0	37.7	42.7	19.1	17.7
AIC	-64.0	**-43.8**	-53.0	**-52.6**	**-53.3**	-50.0	-69.3	-79.5	-32.2	-29.4
AR(2)										
ϕ1	0.943	0.426	0.805	0.585	0.672	0.963	0.576	0.995	1.006	0.639
s.e.	*0.197*	*0.215*	*0.202*	*0.220*	*0.210*	*0.217*	*0.210*	*0.208*	*0.226*	*0.204*
ϕ2	-0.420	0.010 *	-0.346 *	-0.011 *	0.179 *	-0.308 *	0.093 *	-0.354 *	-0.616	-0.353 *
s.e.	*0.194*	*0.215*	*0.205*	*0.233*	*0.228*	*0.247*	*0.232*	*0.277*	*0.262*	*0.250*
Mean	0.183	0.223	0.192	0.200	0.171	0.134	0.099	0.100	0.119	0.234
s.e.	*0.017*	*0.028*	*0.022*	*0.027*	*0.071*	*0.042*	*0.025*	*0.019*	*0.036*	*0.031*
Sigma^2	0.00138	0.00541	0.00302	0.00306	0.00320	0.00360	0.00157	0.00088	0.00711	0.00967
L.hood	37.0	24.9	30.8	29.3	29.9	28.8	37.7	43.6	21.4	18.7
AIC	**-66.1**	-41.8	-53.5	-50.6	-51.9	-49.6	-67.5	-79.1	-34.8	-29.3
MA(1)										
θ1	-0.624	-0.355	-0.565	-0.412	-0.810	-0.892	-0.454	-0.730	-0.881	-0.457
s.e.	*0.137*	*0.167*	*0.185*	*0.150*	*0.292*	*0.180*	*0.160*	*0.151*	*0.159*	*0.149*
Mean	0.182	0.222	0.194	0.202	0.126	0.121	0.091	0.096	0.129	0.239
s.e.	*0.015*	*0.022*	*0.020*	*0.019*	*0.027*	*0.024*	*0.014*	*0.012*	*0.035*	*0.033*
Sigma^2	0.00181	0.00566	0.00367	0.00354	0.00463	0.00366	0.00190	0.00109	0.00755	0.01086
L.hood	34.5	24.5	28.9	28.0	26.1	28.3	35.9	41.5	20.8	17.6
AIC	-63.0	-42.9	-51.8	-50.0	-46.2	**-50.6**	-65.7	-76.9	**-35.5**	-29.1
MA(2)										
θ1	-0.853	-0.407 *	-0.731	-0.569	-0.624	-0.958	-0.772	-0.882	-1.047	-0.694
s.e.	*0.222*	*0.211*	*0.190*	*0.216*	*0.217*	*0.201*	*0.202*	*0.165*	*0.203*	*0.234*
θ2	-0.383	-0.181 *	-1.000	-0.362	-0.541	-0.143 *	-1.000	-1.000	-0.264 *	-0.503
s.e.	*0.174*	*0.191*	*0.277*	*0.170*	*0.194*	*0.201*	*0.386*	*0.272*	*0.218*	*0.239*
Mean	0.184	0.222	0.198	0.201	0.137	0.123	0.089	0.101	0.132	0.244
s.e.	*0.019*	*0.025*	*0.025*	*0.023*	*0.029*	*0.027*	*0.018*	*0.016*	*0.041*	*0.045*
Sigma^2	0.00149	0.00542	0.00191	0.00294	0.00406	0.00364	0.00100	0.00067	0.00719	0.00907
L.hood	36.3	24.9	33.4	29.7	27.6	28.5	40.2	44.4	21.4	19.2
AIC	-64.6	-41.8	**-58.9**	-51.3	-47.2	-49.1	**-72.5**	**-80.8**	-34.7	**-30.3**
ARMA(1,1)										
θ1	-0.353 *	0.015 *	-0.236 *	-0.009 *	0.142 *	-0.657 *	0.101 *	-0.269 *	-0.732	-0.234 *
s.e.	*0.223*	*0.400*	*0.237*	*0.279*	*0.216*	*0.510*	*0.307*	*0.264*	*0.258*	*0.285*
ϕ1	0.506	0.443 *	0.461 *	0.572	0.862	0.346 *	0.694	0.672	0.353 *	0.347 *
s.e.	*0.233*	*0.369*	*0.244*	*0.263*	*0.126*	*0.486*	*0.244*	*0.258*	*0.319*	*0.325*
Mean	0.186	0.223	0.195	0.200	0.167	0.128	0.098	0.105	0.139	0.243
s.e.	*0.023*	*0.027*	*0.027*	*0.028*	*0.067*	*0.035*	*0.025*	*0.025*	*0.049*	*0.041*
Sigma^2	0.00153	0.00541	0.00329	0.00306	0.00324	0.00360	0.00157	0.00091	0.00714	0.01034
L.hood	36.1	24.9	30.0	29.3	29.8	28.7	37.7	43.3	21.4	18.0
AIC	-64.2	-41.8	-51.9	-50.6	-51.7	-49.4	-67.4	-78.5	-34.8	-28.1

Appendix C

Regulatory Uncertainty

C.1 Estimated Parameters

Table 5: Estimators for the Static Transition Probabilities

State	ρ_{01}	ρ_{11}
Alabama	0.059	0.750
Arizona	0.053	0.500
Arkansas	0.056	0.667
California	0.056	0.667
Colorado	0.063	0.800
Connecticut	0.067	0.833
Delaware	0.154	0.875
Florida	0.063	0.800
Georgia	0.063	0.800
Idaho	0.025	0.763
Illinois	0.050	0.250
Indiana	0.071	0.857
Iowa	0.063	0.800
Kansas	0.071	0.857
Kentucky	0.025	0.763
Louisiana	0.091	0.900
Maine	0.053	0.500
Maryland	0.125	0.600
Massachusetts	0.053	0.500
Michigan	0.050	0.250
Minnesota	0.063	0.800
Mississippi	0.063	0.800
Missouri	0.071	0.857
Montana	0.050	0.250
Nebraska	0.025	0.763
Nevada	0.050	0.250
New Hampshire	0.050	0.250
New Jersey	0.056	0.667
New Mexico	0.071	0.857
New York	0.059	0.750
North Carolina	0.071	0.857
North Dakota	0.063	0.800
Ohio	0.071	0.857
Oklahoma	0.091	0.900
Oregon	0.063	0.800
Pennsylvania	0.025	0.763
Rhode Island	0.025	0.763
South Carolina	0.063	0.800
South Dakota	0.050	0.250
Tennessee	0.025	0.763
Texas	0.056	0.667
Utah	0.025	0.763
Vermont	0.071	0.857
Virginia	0.056	0.667
Washington	0.025	0.763
West Virginia	0.025	0.763
Wisconsin	0.025	0.763
Wyoming	0.025	0.763

Table 6: National Uncertainty Fractions

Year	F_t
1990	0.000
1991	0.000
1992	0.104
1993	0.104
1994	0.104
1995	0.188
1996	0.667
1997	0.563
1998	0.521
1999	0.354
2000	0.354
2001	0.146
2002	0.125
2003	0.042
2004	0.042
2005	0.042
2006	0.021
2007	0.042
2008	0.042
2009	0.021
2010	0.021
2011	0.021
μ_F	0.160