Electricity Price Regulation and the Use of Nuclear Power

(DRAFT)

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Abstract

This paper uses a new and unique dataset to identify the causal effect of marginal pricing in electricity markets on planned maintenance outages at U.S. nuclear generating units (NGUs) using reduced-form estimation. The new data are from the Power Reactor Status Reports (PRSRs) that collect a daily snapshot of a NGU's operation including the reactor power level (0-100%) and identify planned maintenance outage periods. Using the PRSRs from 2001-2008, the main regression specification finds that a one degree increase in the maximum daily temperature over 95 degrees (F) yields a 0.105 percentage point decrease in the daily probability of a NGU operating at less than 100% capacity, if the unit can sell electricity under a marginal pricing system (where temperature is used as a proxy for unobserved prices). The NGU can save production costs, as output-reducing maintenance is deferred to lower-demand periods.

Notes: My email addresses is dkarney2@illinois.edu. I am grateful for comments and suggestions from George Deltas, Don Fullerton, and Darren Lubotsky; all remaining errors are my own.

Market prices can help align the incentives of individual economic agents with the interests of society. In wholesale electricity markets, economic theory predicts that marginal pricing leads producers to minimize generation costs. One way producers reduce total cost is to reduce maintenance outages during high-demand periods.

Nuclear generating units (NGUs) have high fixed costs and relatively low marginal costs, and so market pricing during high-demand periods allows them to earn large short-run profits. They can maximize profit by minimizing production outages during high-demand periods. The price signal to minimize outages during high-demand periods is missing from regulated pricing regimes.[1] That is, marginal pricing yields maintenance-allocation efficiency gains over other pricing systems, where they can plan maintenance outages during low-demand periods. The effect is a pure efficiency gain, since no additional resources are used for a given amount of electricity production. The total cost of generation falls because fewer high marginal cost EGUs need to operate to meet demand in peak periods. The existence and size of this maintenance-allocation efficiency gain is an empirical question.

This paper uses a new dataset to identify the causal effect of marginal pricing in electricity markets on the number of planned maintenance outages during high-demand periods at U.S. nuclear generating units (NGUs) using reduced-form estimation. The estimation result is used to calculate the size of the maintenance-allocation efficiency gain. The new data are from the Power Reactor Status Reports (PRSRs) collected by the Nuclear Regulatory Commission (NRC). The PRSRs record a daily snapshot of a NGU's operation, including the reactor power level (0-100%). Importantly, the PRSRs allow the researcher to distinguish among three reasons for a NGU not to be operating at full power: refueling period, unplanned maintenance, and planned maintenance. The maximum daily Summer temperature at nuclear plants help identify periods of peak electricity demand.

Using the PRSRs from 2001-2008, reduced-form estimation finds at that a one degree increase in the maximum temperature during a Summer (June, July, and August) on high temperature days yields a 0.105 percentage point decrease in the probability of a NGU operating at less 100% capacity, if the unit can sell electricity under a marginal pricing system. This means the dollar value of the maintenance-allocation efficiency

[1] Cost-of-service pricing is one type of regulated price system where an electric utility receives a fixed price per unit electricity that is supposed to cover the average cost of generation across a portfolio of EGU-types plus a normal return.

gain is $5.5 million annually (in 2010 dollars). It is unclear how this result can be applied to other types of electricity generating units (EGUs).

The result in this paper provides a lower-bound for the maintenance-allocation efficiency gains due to market pricing in wholesale electricity markets. It would be preferable to identify the effect on *all* U.S. EGUs, but the PRSRs only cover NGUs, and the reduced-form estimation methodology in this paper cannot be extended to all EGUs. Indeed, identifying the maintenance-allocation efficiency gains from marginal pricing at all EGUs requires a detailed structural model.[2]

Other studies find that markets do create efficiencies for U.S. electricity sector. For instance, Kliet and Terrell (2001) find that the average U.S. EGUs would reduce operating costs 13% if the electricity market was deregulated. In addition, Knittel (2002) finds that non-market efficiency incentive programs also lead to reduced fuel costs. In a study of coal-fired power plants in the Eastern U.S., Douglas (2006) finds that wholesale markets reduced costs by 2 to 3 percent.

The paper proceeds as follows. Section 1 provides important background information about the U.S. electric power sector. It describes important characteristics of electricity supply and demand, briefly reviews the history of deregulation and how a wholesale market operates, and discusses the role of nuclear generating units in the electricity sector. Section 2 builds a formal model to show the maintenance-allocation efficiency gains from marginal pricing compared to regulated pricing. Section 3 details the identification strategy to find the causal effect of marginal pricing on the allocation efficiency gains at U.S. nuclear generating units. Section 4 describes and summarizes the multiple datasets used in this paper, including an extensive description of the NRC's Power Reactor Status Reports. Section 5 provides the empirical results. Section 6 adds interpretation of the results and discusses the implications.

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[2] EGUs sometimes do not generate due to a lack of demand and by definition no maintenance-allocative efficiency gains can accrue in such circumstances because no other EGU would need to take the place of unit on maintenance outage in order to meet demand.

1 Background

1.A Supply and Demand

The U.S. Energy Information Agency (EIA) reports that in 2009 the United States power sector had 14,959 EGUs with a total nameplate capacity over 1.046 million megawatts (MW) that produced 3,813.3 billion kilowatt-hours (kWh) of electricity per year. Thus, the U.S. electric power sector had an aggregate annual capacity factor of 42% in 2009, which means that on average less than half of the total available capacity is generating electricity.[3] The inability to store electricity economically and the large variation in electricity demand across seasons leads to the low aggregate annual capacity factor. Furthermore, reserve margin requirements – regulatory minimums for total EGU capacity in service areas – insure that capacity exceeds the maximum expected instantaneous demand, to help prevent black-out and brown-outs. A service area is the geographic region to which an EGU can provide electricity without significant transmission costs.

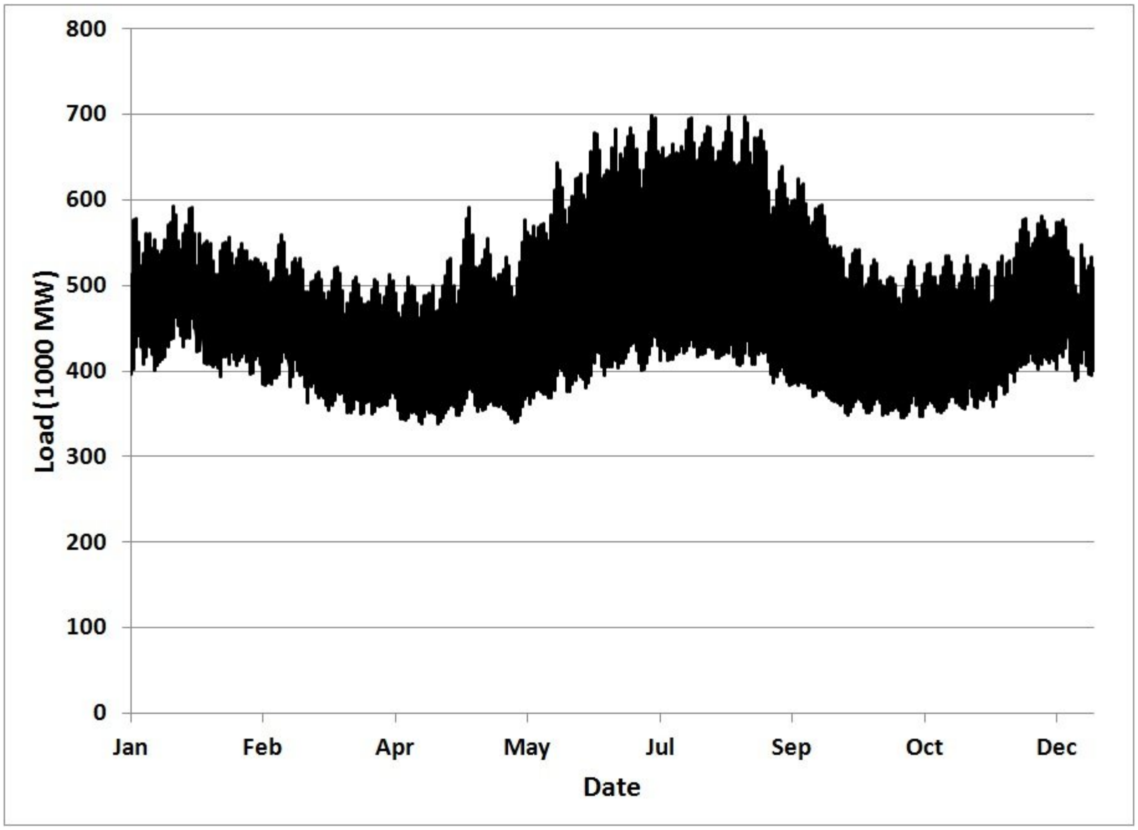
Figure 1 shows the seasonality of electricity demand using 2010 projections from the U.S. Environmental Protection Agency (EPA) for national electricity demand by hour. The vertical axis measures the total national electricity demand in 1000 MWs. Figure 1 demonstrates that electricity demand is highest in Summer (due to increased air-conditioning usage). Demand is lowest in the Spring and Fall due to mild weather, while demand is slightly elevated in the Winter as a result of electric heating used in some parts of the United States. Furthermore, Figure 1 shows considerable daily variability, as electricity usage ebbs in the early morning hours and increases during the late afternoon. It also shows weekly cycles, as electricity usage falls on weekends when many businesses and offices are closed.

As a result of variable demand, together with storage limitations, the electricity power sector deploys a variety of EGU types with different cost and performance characteristics. At one extreme are EGUs with high fixed-cost and relatively low variable-cost known as "baseload" units. These baseload units run at high annual capacity factors in order to spread their fixed costs over many hours of generation. The baseload capacity in many regions of the U.S. is comprised of nuclear-powered, coal-

[3] The annual capacity factor is (Total Generation in Year)/(Total Unit Capacity × Number of Days in Year × 24 hours).

fired, and hydro-electric units. In some U.S. regions, natural gas-fired units called combined-cycle units also add to baseload generation. At the other extreme are EGUs with low fixed-cost and relatively high variable-cost, known as "peaker" units that only operate in high-demand periods and have very low annual capacity factors.

Figure 1: U.S. National Electricity Demand by Hour (2010 Projection)



(Source: U.S. Environmental Protection Agency)

1.B History of Deregulation

Traditionally, the U.S. electric power sector consists of vertically integrated investor-owned utilities that granted monopoly status for their service area by regulators.[4] These regulated monopolies operate the generating units, own the transmission lines, and service customers. Public utility commissions (PUCs) set electricity prices. In general, the prices are set to cover the long-run average cost of the natural monopoly plus economic profit (i.e. cost-of-service pricing). Until the mid-1990s, vertically

[4] See Joskow (2007) for a primer on regulatory reform in the U.S. electricity sector.

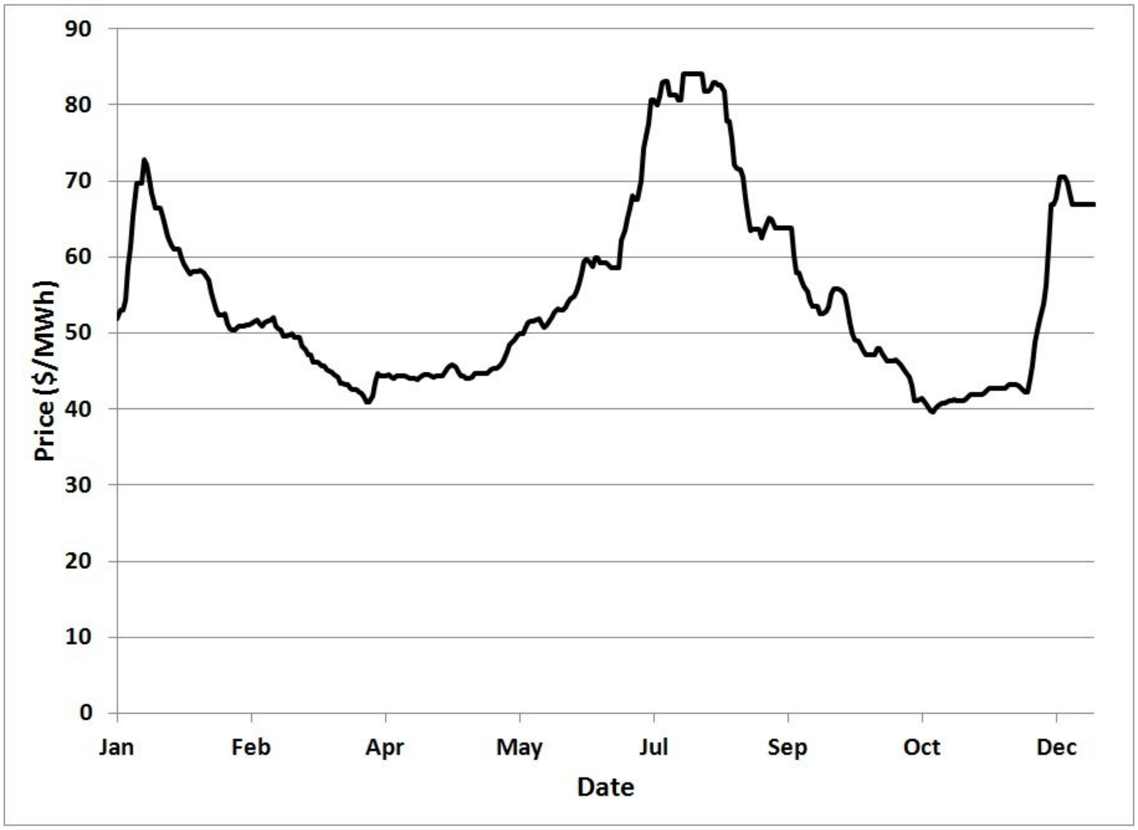
integrated monopolies sold over 90 percent of electricity in the United States [Fabrizio, Rose, and Wolfram (2007)].

During the late-1990s and early-2000s, the U.S. electric power underwent significant restructuring and deregulation. Many vertically integrated utilities were required to sell generating units to non-utility companies and to participate in wholesale electricity market. These markets clear via auction mechanisms where unit operators submit bids indicating at what price they are willing to supply power and then the bids create a supply curve. EGUs dispatch and begin generating electricity when the quantity demand reaches their bid in the supply curve. The marginal unit effectively sets the price per unit of electricity. The regulation or deregulation of electricity utilities occurs at the state level, and thus the United States does not have a uniform regulation of the electric power sector. California's electricity crisis in 2000-2001 led to roll-back of deregulation in many states and a halt to planned deregulation in other states [Borenstein *et. al.* (2002); Wolak (2003)].

The PJM Interconnection in the Eastern U.S. is one of the world's largest wholesale electricity markets.[5] Figure 2 plots a 30-day moving average of peak day-ahead prices in the PJM Interconnection during 2010 (specifically the PJM West Pennsylvania hub). The day-ahead price is a good approximation of the actual price. The figure shows that electricity prices are highest during Summer months and lowest in the Spring and Fall, following pattern of demand in Figure 1. That is, Figure 2 helps demonstrate the positive correlation between seasons and peak electricity prices, since high Summer temperatures increase the demand for electricity. In order to meet the high demand, electric utilities must run the low fixed-cost, high-variable cost "peaker" units.

[5] The acronym "PJM" used to stand for "Pennsylvania-New Jersey-Maryland", but the PJM Interconnection market now includes additional states.

Figure 2: 2010 PJM Interconnection Wholesale Prices (30-day moving average)



(Source: PJM West Pennsylvania Hub prices via EIA Wholesale Data.)

1.C Nuclear Units

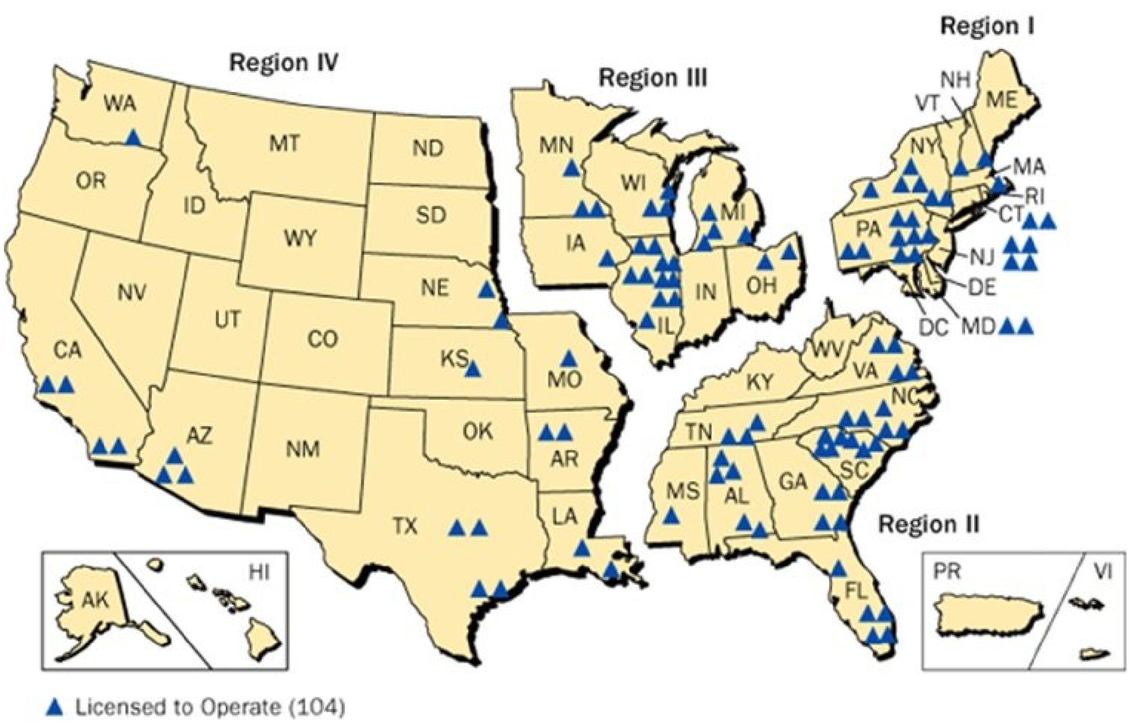
Nuclear generating units are an important part of baseload capacity in the United States, with 104 NGUs located at 66 plants in 31 states (where more than one reactor can be sited at single power plant). Table A-1 in Appendix A lists all operational NGUs with name, state, type, capacity, construction start date, and commercial operation start date. Among the operational U.S. NGU fleet of 104 units, the youngest unit began construction in early-1977 (River Bend-1), and the last unit to become commercially operational occurred in mid-1996 (Watts Bar-1). Important issues in the energy security and climate change policy debates in the U.S. include the relicensing of existing nuclear reactors to extend their operating lifetime and the commissioning of new NGUs.

The approximately 100,000 MW of nuclear capacity constitutes only 10% of total U.S. power sector capacity, but NGUs produced nearly 20% of total electricity in

2009, achieving an annual average capacity factor at 90.4%, a rate much higher than the average EGU. Thus NGUs provide a disproportionate share of total generation compared to their capacity. In addition, an average NGU has a much higher capacity than an average EGU: the average NGU is 970 MW, the average coal-fired unit is 250 MW, the average combined-cycle unit is 125 MW, and the average gas-fired “peaker” units is 25 MW. Thus, if an NGU does not operate on a high-demand day, then nearly 40 “peaker” units must come online to satisfy demand.[6]

Figure 3 shows the spatial distribution of NGUs in the United States. The figure comes from the Nuclear Regulatory Commission, the U.S. federal agency responsible for regulating NGU operations. The four regions in the figure are NRC administrative regions. While the Eastern U.S. has a large concentration of NGUs, Illinois (IL) has the most units (11) with the largest NGU capacity (11,440 MW). However, South Carolina (SC) and Alabama (AL) come first and second, respectively, in capacity per capita. Nuclear power constitutes a large share of capacity and generation in some regions of the country.

Figure 3: Location of U.S. Nuclear Generating Units



(Source: U.S. Nuclear Regulatory Commission)

[6] Source: National Electric Energy Data System (NEEDS) v.4.10

2 Model

This section builds a formal model to show the maintenance-allocation efficiency gains from marginal pricing compared to regulated pricing. The model assumes certainty and only examines the short run, with the number and characteristics of EGUs fixed. In addition, the model addresses neither bidding behavior in a game theoretical structure nor issues of market power.[7] Yet this simple model is enough to demonstrate that marginal pricing creates an incentive to maximize NGU output during high-demand periods by deferring output-reducing maintenance to low-demand periods. Specifically, the opportunity cost of not generating in a high-demand period is larger for a NGU under marginal pricing than under regulated pricing. Furthermore, under regulated pricing a NGU is indifferent between performing output-reducing maintenance in high-demand periods or in low-demand periods. Finally, the model shows that marginal pricing aligns the incentives of the NGU operator with society welfare, since marginal pricing decreases the total cost of generation for a given total quantity demand.

Distinguish three types of EGUs by their marginal cost: very-low (V), low (L), and high (H). The costs are given c_V, c_L, and c_H, where $c_V < c_L < c_H$. Each type has a fixed quantity given by q_V, q_L, and q_H, respectively. The very low-type represents NGUs. Let $S(Q)$ be the supply curve created by ordering EGUs from lowest to highest marginal cost (where Q is the total quantity of electricity supplied). Let D^H and D^L be high and low levels of total demand for electricity, respectively, so $D^L < D^H$. Assume demand is perfectly inelastic, and assume it takes all the low-cost EGUs and some of the medium-cost EGUs to satisfy demand in the low-demand case, but that all those units plus some of the high-cost EGUs are needed to satisfy the high-demand case.[8] Given marginal pricing, $P^H = S(D^H)$ is the high-demand price and $P^L = S(D^L)$ is the low-demand price. Assume the regulated price $\left(P^R\right)$ falls between the high-demand and low-demand prices, $P^L < P^R < P^H$.

[7] Market power can be an important factor, as Mansur (2008) finds that wholesale market inefficiencies brought on by market power can increase costs 3% - 8% above competitive levels.

[8] Recall this model is built to analyze how NGUs perceive the demand, and since NGUs make up a relatively small portion of total capacity and electricity demand always exceeds that capacity. Thus demand from the NGU perspective is always vertical.

Next, assume all NGUs require planned maintenance that takes the unit offline. Also, assume a NGU operator wants to maximize profit and has the ability to schedule planned output-reducing maintenance. Thus, an operator can choose to schedule maintenance either in the high- or low-demand period.

Figure 4 provides a graphical representation of the model. Without lost of generality, assume the first *x* amount of the type-V belongs to a single NGU. In the short-run, profit for this NGU is just the difference between price and marginal cost (given by the supply curve) and multiplied by its capacity. Thus, under marginal pricing and during a high-demand period, the type-V NGU's profit is the area A+B+C in Figure 4, while the marginal profit falls to area C only if demand is low. Meanwhile, given regulated pricing, the NGU's profit is always area B+C, regardless of demand. Therefore, ranking profits finds:

$$\Pi^{M}\left(D^{L}\right) < \Pi^{R}\left(D^{L}\right) = \Pi^{R}\left(D^{H}\right) < \Pi^{M}\left(D^{H}\right) \tag{1}$$

where Π is short-run profit given the demand level, and the superscript denotes regulated (*R*) or marginal (*M*) pricing.

The ranking of short-run profits confirms two facts about the model. First, maximizing profit under marginal pricing requires scheduling output-reducing maintenance for low-demand periods, when not operating has the lowest opportunity cost. Second, profits are the same under regulated pricing regardless of demand.

However, when the NGU of size *x* is unavailable to meet demand, the social cost from increased total generation cost depends only the level of demand and not on the pricing regulation; regardless of the pricing regime, area D is the increased cost of using a type-L unit instead of the type-V unit in the low-demand case, while area E+F+G is the increased cost in the high-demand case (using a type-H unit instead of the type-V unit).[9] The change in total cost (ΔTC) when the NGU of *x* size is unavailable to meet demand can be ranked:

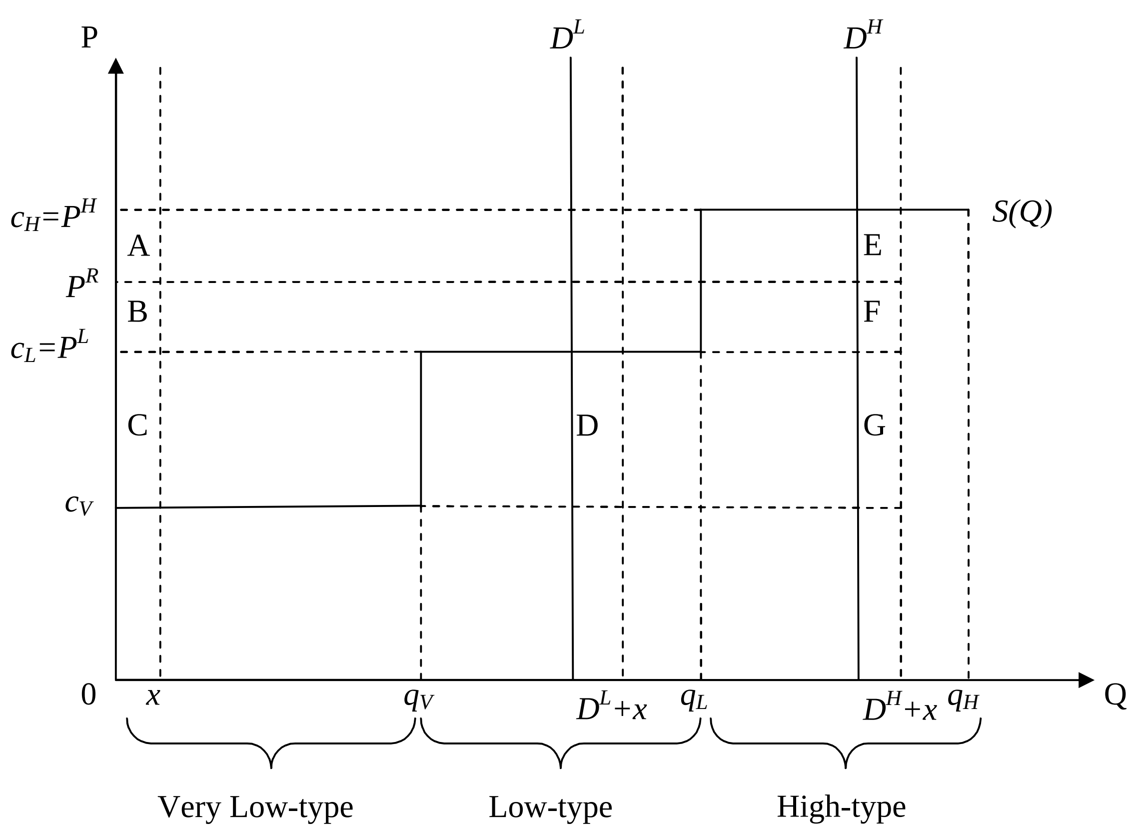
$$\Delta TC^{M}\left(D^{L}\right) = \Delta TC^{R}\left(D^{L}\right) < \Delta TC^{R}\left(D^{H}\right) = \Delta TC^{M}\left(D^{H}\right). \tag{2}$$

[9] Noting areas D and G are the same size in Figure 4.

Comparing expression (2) with (1) shows that marginal pricing aligns the incentives of the NGU operator with society welfare, while regulated pricing does not. Under regulated pricing an operator has the same opportunity cost of maintenance in both demand scenarios $\left(\Pi^R\left(D^L\right)=\Pi^R\left(D^H\right)\right)$, but the social cost of the NGU outage is higher in the high-demand scenario $\left(\Delta TC^R\left(D^H\right)>\Delta TC^R\left(D^L\right)\right)$. Thus, maintenance may occur when it is relatively costly to society. Alternatively stated, marginal pricing offers a low opportunity cost of maintenance in the low-demand period $\left(\Pi^M\left(D^L\right)<\Pi^M\left(D^H\right)\right)$ corresponds with small increases in the total cost of generation $\left(\Delta TC^M\left(D^L\right)<\Delta TC^M\left(D^H\right)\right)$, and therefore aligning the incentives of the NGU operator with the interests of society.

The maintenance-allocation efficiency gain is the reduction in total generation costs when planned maintenance occurs in low-demand periods instead of in high-demand periods.

Figure 4: Model Diagram



3 Identification

This section develops the identification strategy used to determine the causal effect of marginal pricing in electricity markets on the maintenance-allocation efficiency gain at U.S. NGUs. At any particular moment, a given operational electricity generating unit may not generating electricity for many reasons that can be placed into three general categories:

1. **Not Dispatched:** able to generate but does not do so for lack of demand;
2. **Unplanned Outage:** not able to generate, for unplanned reasons such as emergency repairs;
3. **Planned Outage:** not able to generate, for planned reasons, usually related to scheduled maintenance. For nuclear units, refueling the reactor is an example.

NGUs are baseload units with low variable-costs and thus always dispatch when available. That is, when an NGU is not generating, I assume that either a planned or unplanned outage has occurred (hereafter known at the "full-dispatch" assumption). Also, my identification strategy requires that demand and therefore the wholesale price is exogenous for an NGU. Under these assumptions, the ideal experiment to test whether marginal pricing leads to maintenance-allocation efficiency gain can be described as follows. To begin, randomly assign each NGU to either marginal pricing or regulated pricing. Next, measure output at the NGUs as demand varies. The model above predicts in service areas with marginal pricings that high demand and thus high prices provide an incentive for NGUs to decrease output-reducing maintenance in high-demand periods by scheduling planned outages for low-demand periods. However, the ideal experiment did not occur. Instead, deregulation occurred on a state-by-state basis leading to the possibility of selection.[10] Yet, even without the random assignment of the treatment variable, identification of the causal effect of marginal pricing on allocative efficiency is still possible after addressing several issues that complicate the identification.

First, the actual demand for each NGU's service area is unobserved. As a proxy variable to indicate periods of high demand, I use the maximum daily temperature (*MAX*) in Summer months of June, July, and August (where the binary variable *SUMMER* is 1, and 0 otherwise).

[10] One possibility is that NGUs with higher expected profits from marginal pricing lobbied harder for deregulation.

Second, the pricing treatment may not be randomly assigned. However, weather is random and thus serves as exogenous variation in order obtain an unbiased estimate of the maintenance-allocation efficiency gain. In addition, all NGUs were planned long before the beginning of deregulation in the U.S. electricity sector, and thus no strategic building of NGUs to take advantage of market pricing was possible. In fact, actual pricing regulations differ by state, and the full set of regulations are usually more complicated than the dichotomous marginal pricing or regulated pricing. By way of previewing the data section, I use a binary measure called the Exempt Wholesale Generator (*EWG*) status that take the value 1 if a NGU is allowed to sell electricity on a wholesale market (see the complete description of *EWG* below). When *EWG*=1, I interpret this as the NGU participating in a wholesale market with marginal pricing.

Third, the model in section 2 predicts that a higher demand implies a higher opportunity cost of maintenance. Under marginal pricing, however, the relationship between demand and price is not linear due to the shape of the supply curve. Therefore, I apply the non-linear function f(·) to the variable *MAX*, where f(·) may be parametric or non-parametric.

Fourth, nuclear generating units generally operate only at 100% of capacity or at 0% of capacity otherwise; that is, a NGU is usually either “on” or “off”. Thus, it makes sense to define a binary outcome variable to indicate when a NGU is operating at less than 100% output (*L100*) instead of a continuous output variable. In other words, *L100* takes the value 1 if the NGU is operating at less than 100% capacity. In addition, assume that the researcher can identify when a NGU performs planned maintenance, and then define the variable *MAINT* to take the value 1 if *L100*=1 because of planned maintenance.

Therefore, equation (3) is the basic reduced form equation estimated in this paper.

$$\begin{aligned} MAINT = {} & \beta_0 + \beta_1 SUMMER + \beta_2 \mathrm{f}(MAX) + \beta_3 EWG \\ & + \beta_4 SUMMER \times \mathrm{f}(MAX) + \beta_5 SUMMER \times EWG + \beta_6 \mathrm{f}(MAX) \times EWG \\ & + \beta_7 SUMMER \times \mathrm{f}(MAX) \times EWG \end{aligned} \tag{3}$$

The parameter of primary interest is β_7. If a maintenance-allocation efficiency gain exists, then the model can rejects null hypothesis that $\beta_7 \geq 0$, in favor of $\beta_7 < 0$. The implication is that during high-demand periods, if a NGU is an Exempt Wholesale

Generator, then it has fewer instances of operating at less than 100% of capacity due to planned maintenance. The magnitude of β_7 enables one to calculate of the size of the maintenance-allocation efficiency gain.

4 Data

The first part of this section describes the new dataset used here: the NRC's Power Reactor Status Reports. The second part summarizes the auxiliary datasets that provide information about NGU characteristics and temperature.

4.A Power Reactor Status Reports

4.A.1 PRSRs Introduction

The Nuclear Regulatory Commission (NRC) is the Federal agency responsible for regulating commercial nuclear power plants in the United States. The NRC collects daily information between 4 a.m. and 8 a.m. about each of the 104 operational NGUs. Each day, the NRC releases a preliminary Power Reactor Status Report (PRSP) with each unit's reactor power level (0-100%). Additional information is released in a final report after a 28 day lag. I collect the daily PRSPs for all 104 NGUs from 1999-2008, for a total of 379,912 observations. Table 1 describes the fields included in the final daily PRSPs. (Figure A-1 in the Appendix A provides an example of the raw data as found on the NRC's website.)

Table 1: NRC Power Reactor Status Reports (PRSRs) Fields

Name	**Data Type**	**Description**
Date	MM/DD/YYYY	The date of the observation.
Unit Name	Text Field	Unique name for each of the 104 NGUs.
Power Level	Positive Integer (0-100)	Percentage of power reactor operating capacity for that Date.
Down Date	MM/DD/YYYY	If a NGU has a 0 Power Level, Down Date records the beginning Date in the current sequence of 0 Power Level.
Comment	Text Field	Description of the reason why a Power Level is less than 100.
Report Change	Binary (0/1)	Equals 1 if the PRSR changed within the past 24 hours.
Scrams	Positive Integer (0,1,2…)	Number of reactor scrams within past 24 hours, where a "scram" is an unplanned reactor shut-down.

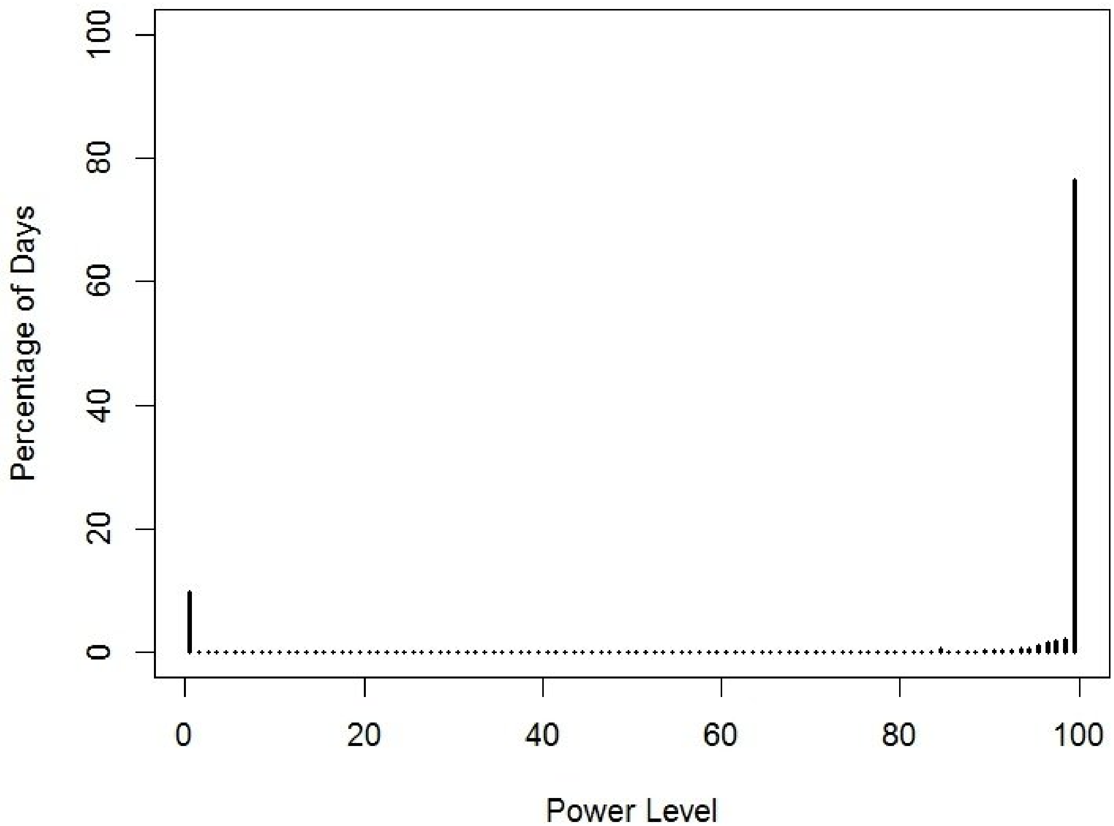
The PRSR Power Level provides a good measure of the daily generation at each NGU despite being observed only once per day. At a monthly aggregate level, official U.S. Energy Information Agency (EIA) generation data confirms that the PRSR Power Level provides a good estimate of total generation. The reason is that EIA generation data at the NGU-level has a 0.995 correlation with PRSR Power Levels converted into electricity output using NGU capacity and summed by month.[11] At the annual aggregate level, total NGU generation calculated using the PRSRs deviate from official EIA data by less than 0.5 percent for every observed year. Also, the PRSRs match know events, such as the black-out that occurred across most of the Northeastern U.S. on August 14, 2003, where PRSRs record reactor scrams at many Northeastern NGUs on that date. A "scram" is an unplanned, immediate shutdown of a nuclear reactor.[12]

Figure 5 plots the percentage of days observed at each Power Level for all NGUs from 1999-2008. The figure shows that NGUs operate at 100 Power Level for nearly 80% of the daily observations, and at 0 Power Level for approximately 10% of the observations. The remaining Power Levels are clustered near the 100% level. Hence, NGUs are generally either entirely "on" at full power or entirely "off". From 1999-2008, the 104 U.S. NGUs had only 23.5% of days with Power Level less than 100 (i.e. *L100*=1).

[11] This correlation statistic only applies for the years 2003-2008, since the EIA did not collect NGU-level generation data for the years 2001-2002.

[12] David *et al.* (1996) finds that after the Three Mile incident, the probability of reactor scrams at U.S. NGUs fell significantly.

Figure 5: Daily U.S. NGU Power Levels (1999-2008)

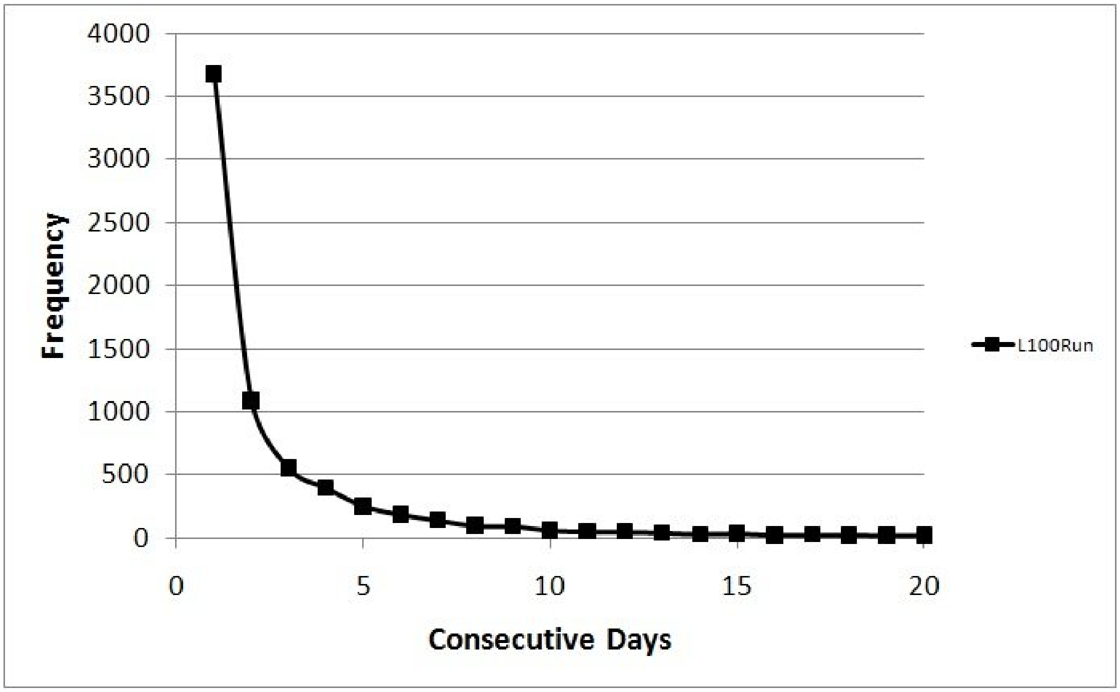


Source: Nuclear Regulatory Commission's Power Reactor Status Reports [with author's calculation].

4.A.2 Time Dependency

The data demonstrate time dependency in the ordering of days with Power Level less than 100. Time dependency comes from lengthy periods of outage when refueling a reactor and multi-day repairs when conducting other maintenance. Thus, the sequencing and duration of days when NGUs operate at level less than maximum power become important characteristics of the data. The 1999-2008 PRSRs report that NGUs had approximately 7700 blocks of consecutive days with *L100*=1 with an average outage period of 11.4 days (where an "outage period" is a number of consecutive days with *L100*=1). However, the median outage period is only 2 days.

Figure 6a: Frequency of Consecutive Days with NGU Power Level Less Than 100% (*L100*=1) for 1-20 Days Runs from 1999-2008

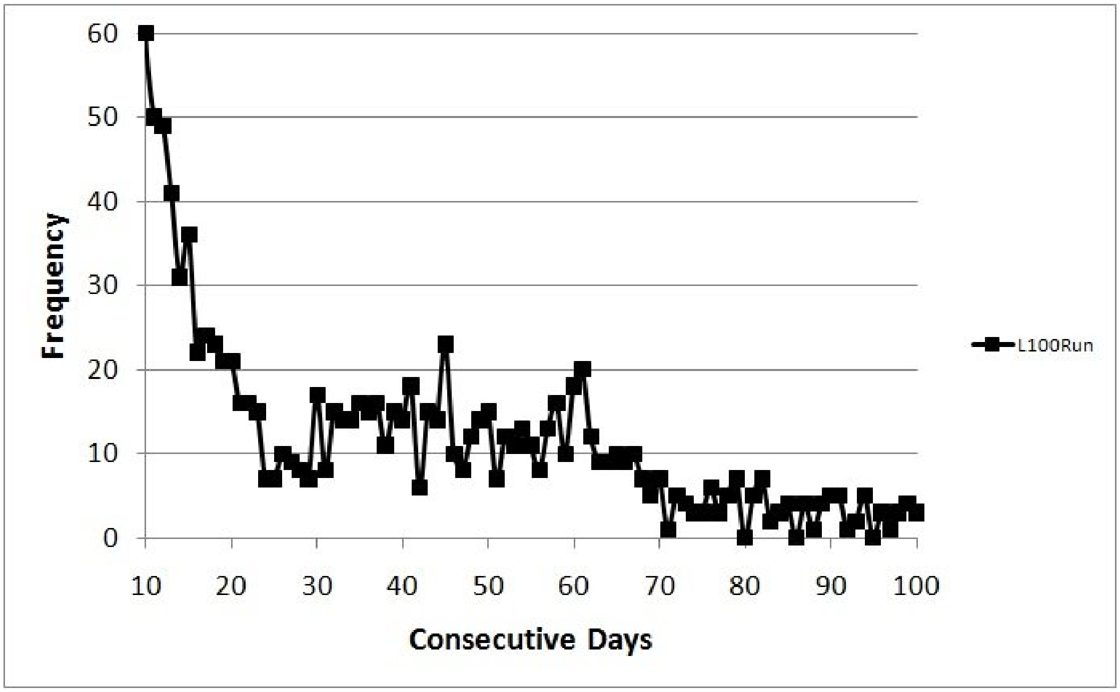


(Source: Nuclear Regulatory Commission's Power Reactor Status Reports [with author's calculation].)

Figure 6a counts the frequency of consecutive days at NGUs with Power Level less than 100%, with durations of 1 to 20 days.[13] I find that almost 70% of the outage periods last 1-3 days, but these periods account for less than 10% of the total outage days. The vertical scale of Figure 6a makes it difficult to gauge the frequency of outages periods from 5 to 20 days. Thus, figure 4b records the frequency of outage periods with runs of 10 to 100 days (providing overlap for outage periods 10-20 across the figures). Figure 6b shows many outage periods lasting longer than 10 days. Interestingly, the same number of total outage days occurs in outage periods lasting 10-30 days as in periods lasting 1-3 days. Not included in figures 6a or 6b, the 1999-2008 PRSR data have 118 outage periods longer than 100 consecutive days. To account for this time dependency, the main estimation equation below contains a binary variable indicating if the previous day's Power Level was less than 100% (using a variable called *LagL100*).

[13] When calculating the consecutive days in an outage period, the outages for a portion of the days at the beginning and end of the period maybe truncated.

Figure 6b: Frequency of Consecutive Days with NGU Power Level Less Than 100% (*L100*=1) for 10-100 Days Runs from 1999-2008



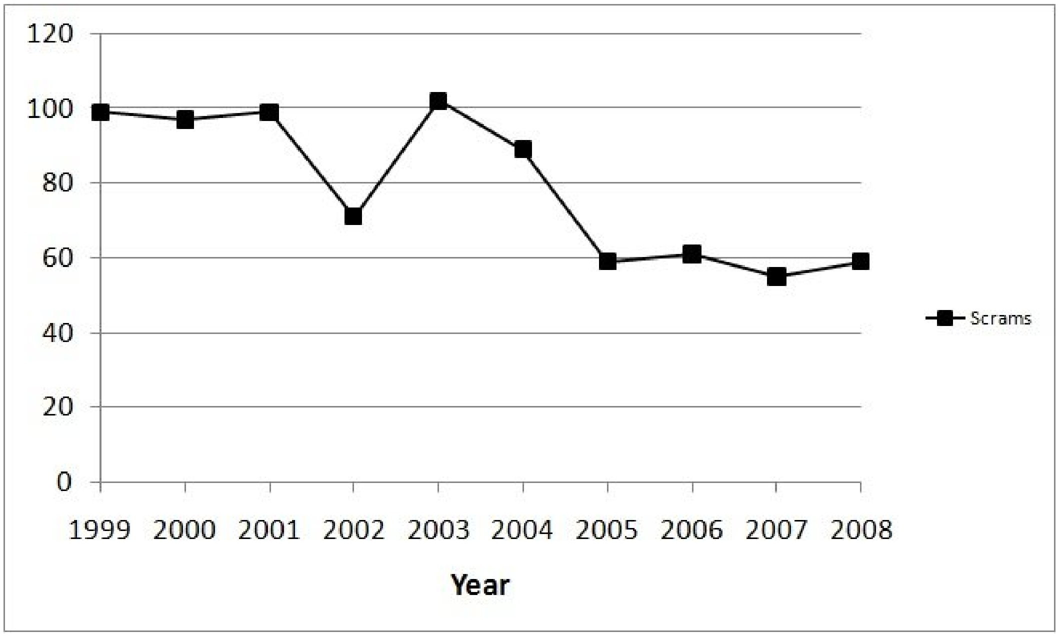
(Source: Nuclear Regulatory Commission's Power Reactor Status Reports [with author's calculation].)

4.A.3 Categorizing Outages

The other fields in the final PRSRs allow the categorization of Power Levels below 100% into three groups: unplanned outage, fuel cycle, and planned maintenance.

Unplanned outage is the first and easiest group to determine, as 70% of all unplanned outages begin with a reactor scram [Rothwell (1990)]. Therefore, the Scrams field in the PRSRs provides a good approximation for unplanned outages at NGUs. Define the variable *SCRAM* as a binary variable equal to 1 if *L100*=1 and the Scram field is non-zero (indicating at least one scram occurred in the past 24 hours). The PRSRs records that from 1999-2008 U.S. NGUs averaged almost 80 scrams per year or nearly one scram every 5 days. Also, reactor scrams occur during the refueling process as reactors comes back online, and the data show that 18.3% of scrams occur during refueling periods. Figure 7 plots the number of reactor scrams by year (counting multiple scrams occurring with each 24 hour period). The figure indicates a possible downward trend in the frequency of scrams at U.S. NGUs. The peak number of scrams occurred in 2001 with 102 scrams across all reactors.

Figure 7: Number of Reactor Scrams Across All NGUs by Year (1999-2008)

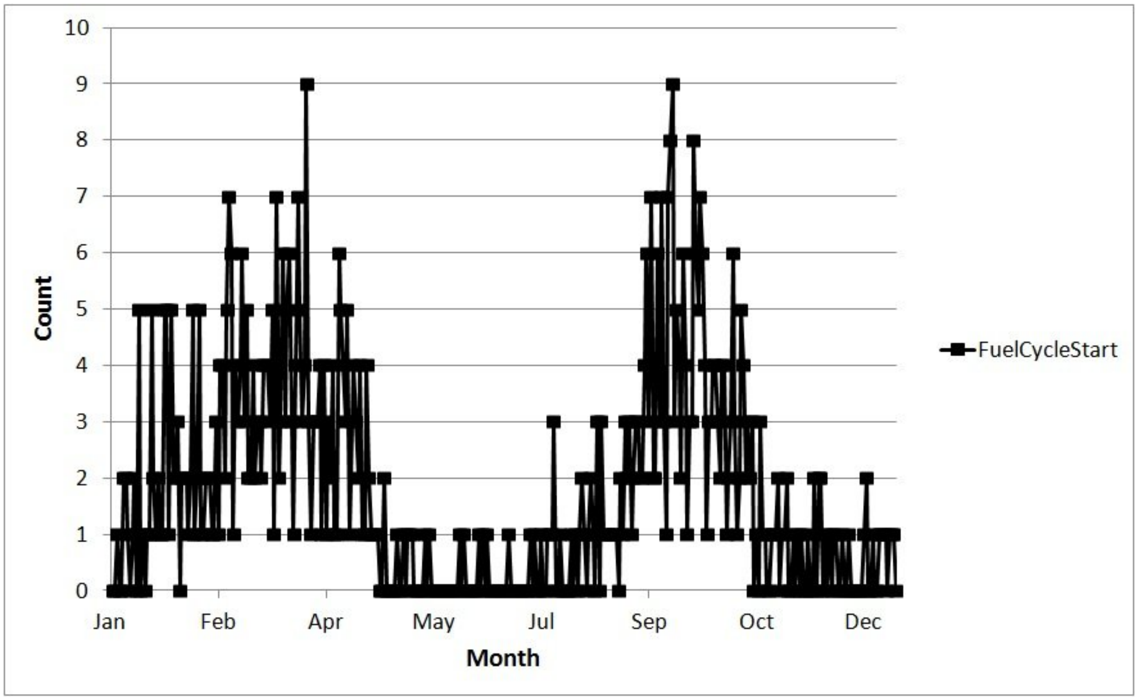


(Source: Nuclear Regulatory Commission's Power Reactor Status Reports [with author's calculation].)

The fuel cycle is the next and most difficult group to identify. Refueling a reactor is a planned event that can take weeks to complete, where the reactor needs to be shut down and fuel rods removed and replaced. The basic methodology to identify a refueling period is to search the Comments field in the PRSRs to find words like "refuel" (recalling that the Comment field only contains information if the Power Level is less than 100%). Next, assign all concurrently adjacent days with *L100*=1 to be in the same fuel cycle, and define the binary variable *FUEL*=1 if a NGU is in a fuel cycle (where all fuel cycles below 10 days and above 50 days were hand checked for accuracy). The data reveal that from 1999-2008 the 104 U.S. NGUs conducted approximately one fuel cycle every 1.5 years, with a median outage period of 56 days during refueling. The start date of refueling periods demonstrates strong seasonality. Figure 8 plots the frequency of start dates of refueling periods. Observe that Figure 8 is the inverse image of Figure 1; that is, low-demand periods in the Fall and Spring coincide with refueling period start dates.[14]

Figure 8: Frequency of Refueling Start-Dates at U.S. NGUs (1999-2008)

[14] Some observations with 100% Power Level are classified as *FUEL*=1 so that NGUs have uninterrupted refueling cycles. An NGU may begin cooling down the reactor then go back up to 100% of capacity for a few days, and then restart the cooling down process again.



(Source: Nuclear Regulatory Commission's Power Reactor Status Reports [with author's calculation].)

The final group consists of all observations where a NGU is not at 100% Power Level and not classified as either *SCRAM=1* or *FUEL=1*. Since these outages are neither unplanned outages due to scrams nor refueling periods, then all remaining outages must be planned maintenance.[15] Thus, I define the binary variable *MAINT* to take the value 1 if *L100*=1 and *SCRAM*=0 and *FUEL*=0. From 1999-2008, the median U.S. NGU has 23 days per year classified as *MAINT*=1.

In summary, I use the PRSPs to generate four variables. Table 2 provides a brief description of these binary variables as well as summary data. The table shows that an NGU is refueling a narrow majority of the time when its reactor has a Power Level less than 100%. However, planned maintenance is an important reason why a NGU may be operating at less than 100% of capacity.

[15] Here, I implicitly assume all unplanned outages are accurately measured by the *SCRAM* variable. If this measurement error is not correlated with pricing regime, then the point estimate for the maintenance-allocation efficiency gain is still unbiased.

Table 2: Binary Variable Categories Generated from PRSPs (1999-2008)

Variable Name	Fraction (%)	Description
L100	23.5	1 if Power Level less than 100%, and 0 otherwise
SCRAM	0.2	1 if Power Level less than 100% and Scrams non-zero, and 0 otherwise
FUEL	12.4	1 if Power Level less than 100% and Comment contains words like "refuel", indicating the NGU is refueling its reactor, and 0 otherwise.
MAINT	11.0	1 if Power Level less than 100% and not categorized as *SCRAM* or *FUEL*, and 0 otherwise
# Obs.	379912	

Notes: A NGU may have *SCRAM*=1 and *FUEL*=1 for the same observation date. In some instances, *FUEL*=1 when *L100*=0. Source: Nuclear Regulatory Commission's Power Reactor Status Reports [with author's calculation].

4.B Other Datasets

I combine three additional datasets with the Power Reactor Status Reports (RPSRs) to form the final dataset used in the econometric analysis.

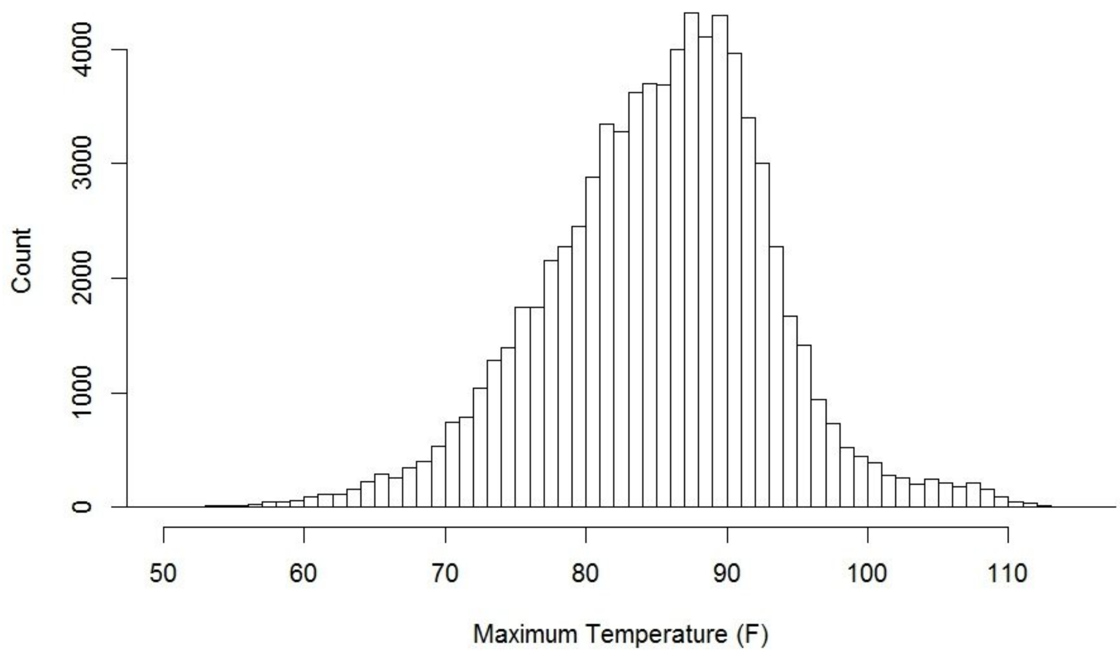
4.B.1 NRC Unit-Level Data

A series of unit-level characteristics come from the NGU roster provided by the Nuclear Regulatory Commission including the construction start date, commercial operation start date, unit capacity (MW), and reactor type (see Table A-1 in Appendix A). Other useful NRC data include the reactor containment type, supplier, reactor design, architectural firm, construction firm, commercial operation license expiration date, and NRC regulatory region. In addition, I derive a series of unit-level variable from the underlying NCR data. These constructed variables are NGU age, a binary indicator if unit has the same architectural firm and construction firm, length between a units construction start and the earliest unit's construction start date, length of unit's construction, and a binary indicator if a NGU started commercial operation after the Three Mile reactor meltdown. All of these variables help control differences across NGUs. For instance, an older NGU might require more maintenance per year than a newer NGU.

4.B.2 NOAA Temperature Data

This paper uses the maximum daily temperature in the Summer as a proxy for electricity demand.[16] Temperature data from the U.S. National Oceanographic and Atmospheric Administration (NOAA) provides daily maximum temperature at weather stations across the United States. I map each NGU to the closest weather station using longitude and latitude coordinates. Define the variable *MAX* as the maximum daily temperature in hundredths of degrees Fahrenheit observed at an NGU Figure 9 plots the frequency of maximum daily temperatures at U.S. NGUs from 1999-2008 using the mapped NOAA data. The histogram resembles a normal distribution, but with more mass at lower maximum temperatures due to the unequal distribution of NGUs across geographic locations (see Figure 3).

Figure 9: Frequency of Maximum Daily Summer (June, July, and August) Temperatures at U.S. NGUs (1999-2008)



Source: NOAA (with author's calculations)

Recall that equation (4) allows for a non-linear function of the maximum daily temperature, called f(*MAX*). The main specification in this paper use a non-parametric,

[16] High Summer temperature induce high electricity demand due to air conditioning usage.

non-linear function defined by grouping observation by ranges of temperature and creating a series of dummy variables indicating the group to which an observation belongs. I define the groups such that approximately 10% of the observations from each tail of the temperature distribution are assigned to the lowest and highest temperature groups. Table 3 shows the chosen temperature groups and reports the percentage of Summer temperature observations that fall within each group. For example, group 6 contains all the observations where *MAX* is greater than or equal to 95 degrees F. The data show that 10.56% of the observations are in group 6.

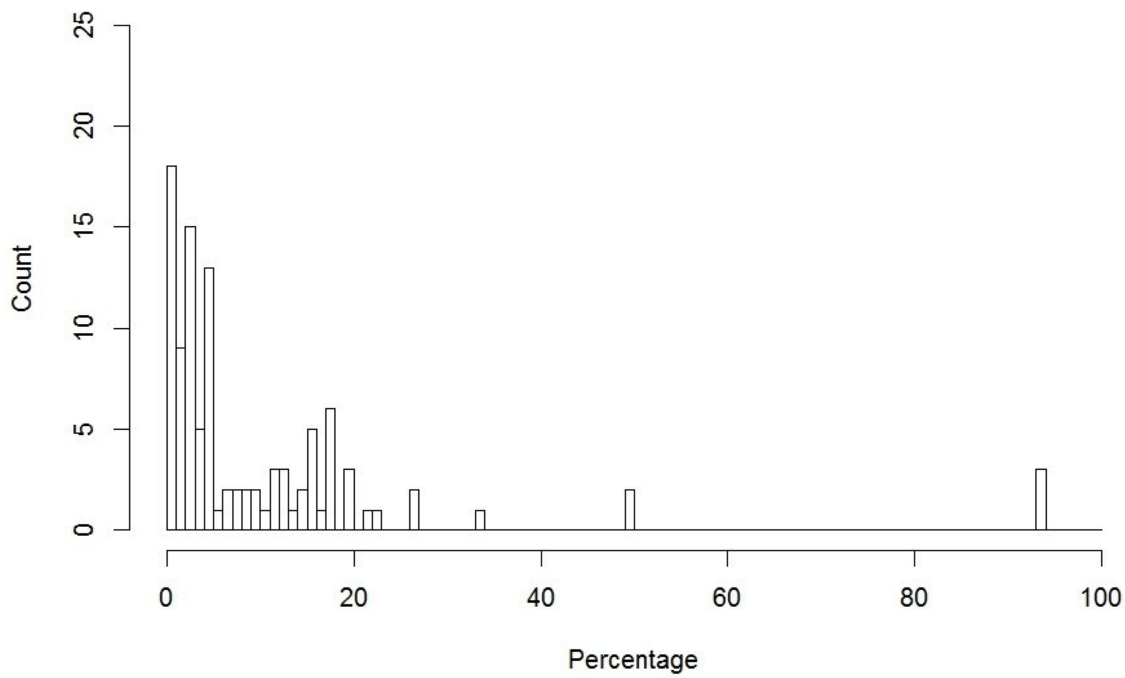
Table 3: Temperature Group Definitions

Group	Temperature Range (F)	Percentage of Summer Temperature Observation within Group
1	(·,75)	8.89
2	[75,80)	12.18
3	[80,85)	20.38
4	[85,90)	25.88
5	[90,95)	21.12
6	[95,·)	10.56

Note: Cells subject to independent rounding.

Finally, since NGUs have an unequal distribution across geographic locations, then NGUs are not necessarily equally represented across temperature groups. Figure 10 shows the distribution of NGUs within group 6 (95 degrees or above). It plots the percentage of a NGU's total observations in the Summer that fall within that group's temperature range. The figure shows that 3 units have over 90% of their Summer *MAX* observations in group 6, where these three units are located at the same plant in Arizona. The figure also shows that 2 units have nearly 50% of their Summer *MAX* observations in group 6 (at a plant in Texas). The main estimation results include the 5 units with high group 6 percentages, but estimates from regressions that omit these units find no statistical difference in outcomes. All NGUs have some observations in temperature group 6; that is, no NGU has zero observations in group 6.

Figure 10: Distribution of the Percentage of U.S. NGUs Observations for Maximum Summer Temperatures of 95 degrees (F) or Higher (1999-2008)



4.B.3 EIA Regulatory and Ownership Data

Finally, and most importantly, the U.S. Energy Information Agency (EIA) Form-860 records whether a NGU is an Exempt Wholesale Generator (EWG) starting in 2001. An EWG is a regulatory status granted by the Federal Energy Regulatory Commission (FERC). FERC defines an EWG as an entity that can "generate and sell electricity at wholesale without being regulated as utilities under [Public Utility Regulatory Policies Act of 1978]".[17] Another source states that "[a]n Exempt Wholesale Generator may sell [energy] to publicly-owned municipal utilities, but their exemption allows them to sell - or not sell - energy to whomever they choose at whatever rate they choose."[18] I use the EWG status of a NGU as the measure of whether each unit can sell its energy in a wholesale market (as opposed to receiving a regulated rate). In 2001, 15 NGUs had EWG status in 5 states (MA, MD, NJ, NY, PA). By 2008, 18 NGUs had EWG status

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[17] Link: http://www.ferc.gov/students/energyweregulate/fedacts.htm

[18] Link: http://www.energyvortex.com/energydictionary/exempt_wholesale_generator_%28ewg%29.html This source also notes that "The exemption applies federally, but is usually subject to approval by state and regional bodies who may override the exemption if it is felt that this is in the public interest and require a generator to sell within a certain price range or to a certain customer or group of customers."

across 4 additional states (MI, NH, VT, WI).[19] See Data Appendix Table A-2 for the complete EIA Form-860 data. Define the binary variable *EWG*=1 if a NGU is an Exempt Wholesale Generator in a given year.

Table 4 provides 2008 summary statistics of the final dataset, separated into columns by NGUs' Exempt Wholesale Generator status. The final dataset is limited to the years 2001-2008 by the date range of EIA Form-860. This table show that the EWGs are less numerous, older, and smaller (although none of these differences are statistically significant). However, EWGs have a higher average Power Level (92.7%) and fewer days with Power Levels less than 100% (65.1). Interestingly, Table 4 shows that the difference in *L100* days between the EWG and Non-EWG columns is driven by the *MAINT* category, where EWG have almost 20 fewer *MAINT* days, despite being older units on average.

[19] According to EIA Form-860, one NGU (Three Mile Island #2 in PA) lost its EWG status between 2001 and 2008.

Table 4: NGU Summary Statistics for the Year 2008 by EWG Status

Variable	Exempt Wholesale Generator (EWG)	Non-Exempt Wholesale Generator
Panel A: Annual Data		
Num. Units	18	86
Average Age (Years)	31.5 [6.0]	27.8 [6.5]
Average Size (MW)	901.6 [239.6]	983.7 [212.2]
Average Power Level (Percent)	92.7 [24.3]	89.3 [29.4]
Average *L100* (Number)	65.1 [140.0]	88.3 [156.6]
Average *SCRAM* (Number)	0.3 [11.0]	0.6 [15.0]
Average *FUEL* (Number)	40.8 [115.2]	44.2 [119.3]
Average *MAINT* (Number)	24.7 [91.8]	44.0 [119.0]
Panel B: Summer Only (June, July, & August)		
Average Power Level (Percent)	98.2 [8.9]	97.0 [15.1]
Average *L100* (Number)	17.9 [36.4]	14.3 [33.3]
Average *SCRAM* (Number)	0.0 [0.0]	0.2 [3.7]
Average *FUEL* (Number)	7.2 [24.8]	2.7 [15.5]
Average *MAINT* (Number)	11.1 [29.9]	11.5 [30.4]

Notes: Standard deviations in brackets. A NGU may have *SCRAM*=1 and *FUEL*=1 for the same observation date. In some instances, *FUEL*=1 when *L100*=0.

5 Results

5.A Main Estimation

The main estimation equation is given by:

$$\begin{aligned} Y_{it} &= \beta_0 + \beta_1 SUMMER_t + \beta_2 \mathrm{f}\left(MAX\right)_{it} + \beta_3 EWG_{it} \\ &+ \beta_4 SUMMER_t \times \mathrm{f}\left(MAX\right)_{it} + \beta_5 SUMMER_t \times EWG_{it} + \beta_6 \mathrm{f}\left(MAX\right)_{it} \times EWG_{it} \\ &+ \beta_7 SUMMER_t \times \mathrm{f}\left(MAX\right)_{it} \times EWG_{it} \\ &+ \beta_8 LagL100_{it} + \beta_9 Plant_j + e_{it} \end{aligned} \tag{4}$$

where equation (4) is similar to equation (3), and follows from the identification strategy outlined in section 3. It is a linear probability model where the dependent variable (Y_{it}) can be any of the four dependent variables found in table 2, for NGU i, plant j, and day t. I focus on results when Y_{it}=*MAINT*, since the goal is to identify the maintenance-allocation efficiency gains. The other dependent variables act as falsification tests.

The main specification uses the temperature groups defined in table 3. In addition, equation (3) includes the lag of *L100*, because the dependent variables exhibit time dependency (see section 4). Finally, plant-level fixed effects account for any anomalies with the mapping of NOAA temperature data to the NGUs, since all NGUs at the same plant receive temperature (and clustering of the standard error also occurs at the plant-level). As Wooldridge (2002, p.330) states, "The strict exogeneity assumption in the model requires that the error [e_{it}] be uncorrelated with the explanatory variables for all units within cluster [j]. This assumption is often reasonable when a cluster effect [$Plant_j$] is explicitly included. (In other words, we assume strict exogeneity conditional on [$Plant_j$].)"

Table 5 reports the baseline estimation results using equation (4), where columns [1]-[4] contain the name of the dependent variable. The estimated coefficient on $SUMMER \times MAX \times EWG$ is used to calculate the maintenance-allocation efficiency gain when Y_{it}=*MAINT*. Table 5 reports its value for each temperature group, where group 1 is the reference group (and thus omitted). All of the lower-level cross-product and plant-level fixed-effects estimates are omitted. Also, recall that the final dataset only includes years 2001-8 due to data limitation for the Exempt Wholesale Generation status variable, leaving 303,888 observations across the 104 NGUs.

Table 5 column 4 reports results when the dependent variable is *MAINT*. The estimate of -0.754 for *TempGroup6* is statistically significant and means high temperature observations are correlated with a reduction in planned maintenance at *all* NGUs (whether regulated or marginal pricing). However, the estimate for *SUMMER* × *MAX* × *EWG* × *TempGroup6* of -10.52 is also statistically significant and implies that marginal pricing does lead to even less planned outages on the very high temperature days – in other words, maintenance-allocation efficiency gains. Since *MAX* is measured in hundredths of degrees, the estimate -10.52 means that a one degree increase in the maximum Summer daily temperature for that group (group 6) reduces the probability of planned maintenance at those NGUs by 0.105 percentage points, if the NGU has Exempt Wholesale Generator status and thus can sell electricity in a wholesale market. The lower temperature groups do not exhibit evidence of the maintenance-allocation efficiency gain, a result consistent with a non-linear relationship between demand and price. The next section details, this reduction in planned outage translates to a $5.5 million annual maintenance-allocation efficiency gain, if all NGUs were under marginal pricing rather than regulated pricing.

Table 5 column 2 reports results when the dependent variable is *SCRAM*. The model finds a statistically significant increase in the probability of a reactor scram during high demand if a NGU is an EWG (see *SUMMER* × *MAX* × *EWG* × *TempGroup6* equal to 2.04). This result is surprising, as scrams are usually seen as random events, but if a NGU defers maintenance in order to earn large short-run profits allowed by marginal pricing, then perhaps a reactor scram is more likely. Table 5 columns 1 and 3 respectively report with the dependent variable is *L100* and *FUEL*, respectively. Essentially, *L100* is a combination of the other three dependent variables, and so its coefficient estimates are close to the sum of the coefficient estimates from the other three models. The coefficient on *FUEL* does not show any fuel cycle reductions during high demand periods, but that result comes from the fact that a NGU cannot just restart immediately during a fuel cycle, an interpretation corroborated by the size of the *LagL100* estimate.

Figure 11 helps visualize the results from Table 5. The figure plots the *SUMMER* × *MAX* × *EWG* coefficient estimate for each temperature group for the model with *MAINT* as the dependent variable. The solid black line is the average effect, while the dashed lines indicate the 95% confidence interval. As expected, Figure 11 shows the large decrease in planned maintenance probability that occurs in temperature group 6. The overall interpretation of the results in Table 5 is consistent with finding maintenance-allocation efficiency gains at U.S. NGUs caused by marginal pricing.

5.B Interpreting Coefficients

Recall that the baseline estimate of -10.54 for *SUMMER* × *MAX* × *EWG* × *TempGroup6* means that that a one degree increase in the maximum Summer daily temperature reduces the probability of planned maintenance at a NGU by 0.105 percentage points, if the NGU has Exempt Wholesale Generator status. However, this estimate is difficult to interpret. This section aids in the interpretation of the estimated probability and tries to calculate a dollar value for the maintenance-allocation efficiency gains.

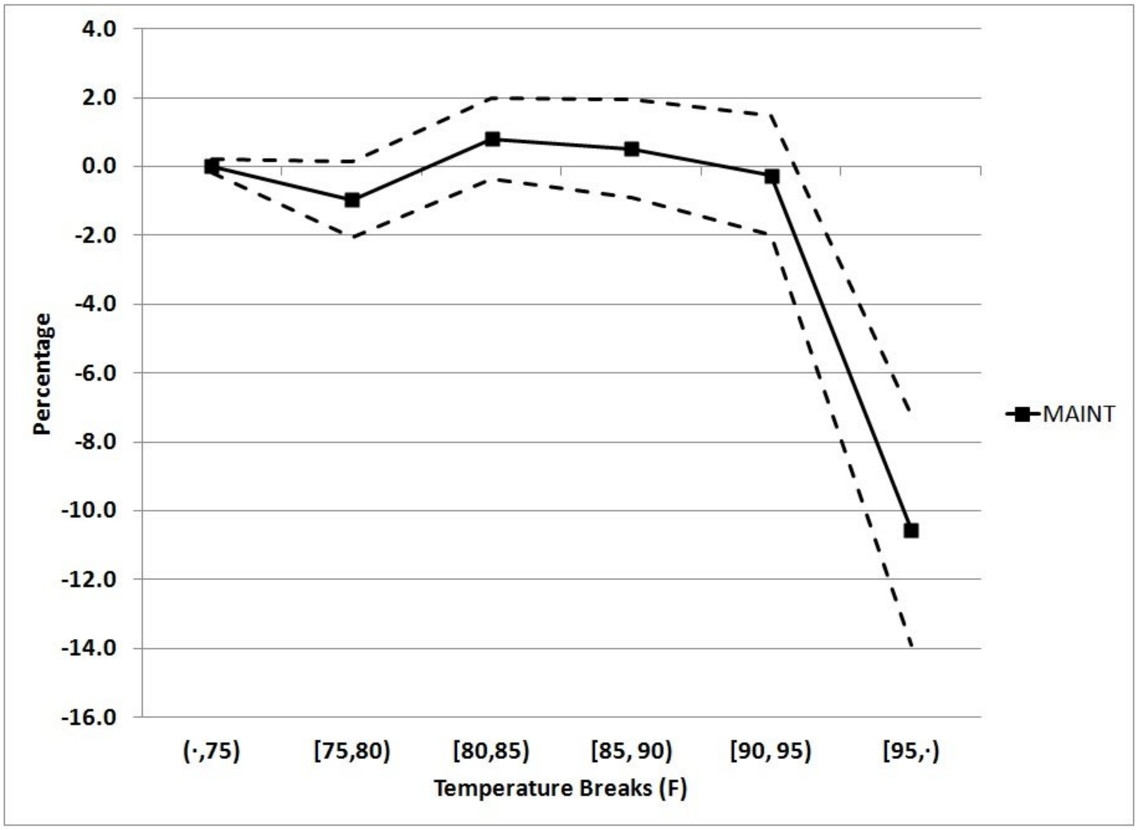
To begin, note that the Summer months (June, July, and August) have 91 potential days of operation. However, NGUs already average 11.46 days per Summer of planned outages (from 2001-2008), and thus U.S. NGUs have approximately 81 days of operation where planned maintenance did not occur (since 91 × (1 – 0.1146) = 80.6). Next, the mean Summer temperature for temperature group 6 is 99.2 degrees F, with a standard deviation of 4.48 degrees (derived from the variable *MAX* using the 10.56 percent of observation in the group). Applying a 4.48 degree increase to the above estimate means that a one standard deviation yields a 0.47 percentage point decrease in planned outage probability (0.105 × 4.48 = 0.47). A 0.47 percentage point daily probability of an event means that the event occurs on average once every 213 days. Finally, divide the 81 at-risk days for planned outages by the 213 days on average between each eliminated planned outage, and multiply the percentage of observations in temperature group 6 (10.56%) and the number of NGUs (104), to find that 4.2 planned outage days would be eliminated each Summer across all NGU under universal marginal pricing.

Table 6: Baseline Results (with lower-level cross-product and plant-level fixed-effects estimates omitted)

Independent \ Dependent	*L100* [1]	*SCRAM* [2]	*FUEL* [3]	*MAINT* [4]
INTERCEPT	0.046*** [0.005]	0.001* [0.001]	0.112 [0.023]	-0.060** [0.019]
SUMMER	-0.028 [0.030]	-0.006 [0.004]	-0.028 [0.074]	0.002 [0.069]
MAX	0.021** [0.008]	0.001 [0.001]	0.053 [0.031]	-0.038 [0.023]
EWG	-0.007 [0.006]	0.000 [0.001]	-0.002 [0.028]	-0.007 [0.024]
TempGroup2	-0.062 [0.083]	0.010 [0.018]	-0.111 [0.092]	0.031 [0.114]
TempGroup3	-0.075 [0.092]	0.000 [0.022]	-0.113 [0.102]	0.024 [0.089]
TempGroup4	0.117 [0.096]	-0.022 [0.022]	0.077 [0.161]	0.037 [0.175]
TempGroup5	-0.005 [0.200]	0.021 [0.025]	0.039 [0.404]	-0.037 [0.389]
TempGroup6	-0.023 [0.124]	0.006 [0.016]	0.722 [0.165]	-0.754*** [0.228]
LAGL100	0.866*** [0.007]	0.001*** [0.000]	0.561*** [0.030]	0.304*** [0.028]
SUMMER* × *MAX* × *EWG	-0.082° [0.048]	-0.030*** [0.006]	-0.070 [0.111]	0.012 [0.103]
SUMMER* × *MAX* × *EWG* × *TempGroup2	0.100 [0.450]	0.185 [0.116]	1.108** [0.386]	-0.980 [0.571]
SUMMER* × *MAX* × *EWG* × *TempGroup3	0.335 [0.389]	0.053 [0.106]	-0.470 [0.528]	0.795 [0.593]
SUMMER* × *MAX* × *EWG* × *TempGroup4	0.562 [0.396]	0.180 [0.156]	-0.074 [0.629]	0.529 [0.723]
SUMMER* × *MAX* × *EWG* × *TempGroup5	-0.123 [0.453]	0.034 [0.126]	0.101 [0.921]	-0.294 [0.875]
SUMMER* × *MAX* × *EWG* × *TempGroup6	-7.908** [2.794]	2.04* [0.876]	0.562 [1.167]	-10.52*** [1.695]
Adjusted R-squared	0.798	0.001	0.488	0.393
# Observations	303,888	303,888	303,888	303,888

Notes: '°' indicates significant at 0.10 level; * indicates significant at 0.05 level; ** indicates significant at 0.01 level; *** indicates significant at 0.001 level. Many of the cross-product and plant-level fixed effect estimates are omitted. The standard errors are below the parameter estimates in brackets and clustered at the plant-level. Cells are subject to independent rounding.

Figure 11: ***SUMMER* × *MAX* × *EWG* for each Temperature Group with Dependent Variable *MAINT***



The next step is to convert outage days into cost. The variable operating cost (excluding fuel) of U.S. NGUs is on average is 0.78 mills/kWh in 2010 dollars [U.S. EPA (2006)]. Meanwhile, the variable operating cost of combined turbine "peaker" units range from 2.75 – 10.11 mills/kWh in 2010 dollars (with a non-weighted average of 6.43 mills/kWh) [U.S. EPA (2006)]. Thus, the difference in variable operating cost between a NGU and "peaker" unit is 5.65 mills/kWh, where a "mill" is a tenth of a cent. Recall, an average NGU has a capacity of 970 MW, while the average gas-fired "peaker" unit is only 25 MW. Thus, if an NGU does not operate on a high-demand day, then it take nearly 40 "peaker" units coming online to satisfy that demand. Therefore, a NGU missing one hour of peak demand increases total electricity costs by nearly $220,000 (1 hour × 970 MW × (1000 kWh / 1 MWh) × (40 × 5.65 mills/kWh) × (1$ / 1000mills) = $219,220). Assume each day with a maximum daily temperature in temperature group 6 has six hours per day where "peaker" units are needed to meet demand. So, multiply the number of reduced planned outage days (4.2) times the cost per hour to fill demand by “peakers” ($219,220) times six hours per day, to find a maintenance-allocation efficiency gain of $5.5 million dollars per year (if all U.S. NGU were in wholesale markets compared to all under regulated pricing). In contrast, the total U.S. retail electricity sales in 2008 were approximately $370 billion dollars, although the estimate of the maintenance-allocation efficiency gains in this paper apply only to NGUs and cannot directly be extended to other electricity generating units. However, it is likely that maintenance-allocation efficiency gains do accrue at all EGUs that participate in wholesale markets.

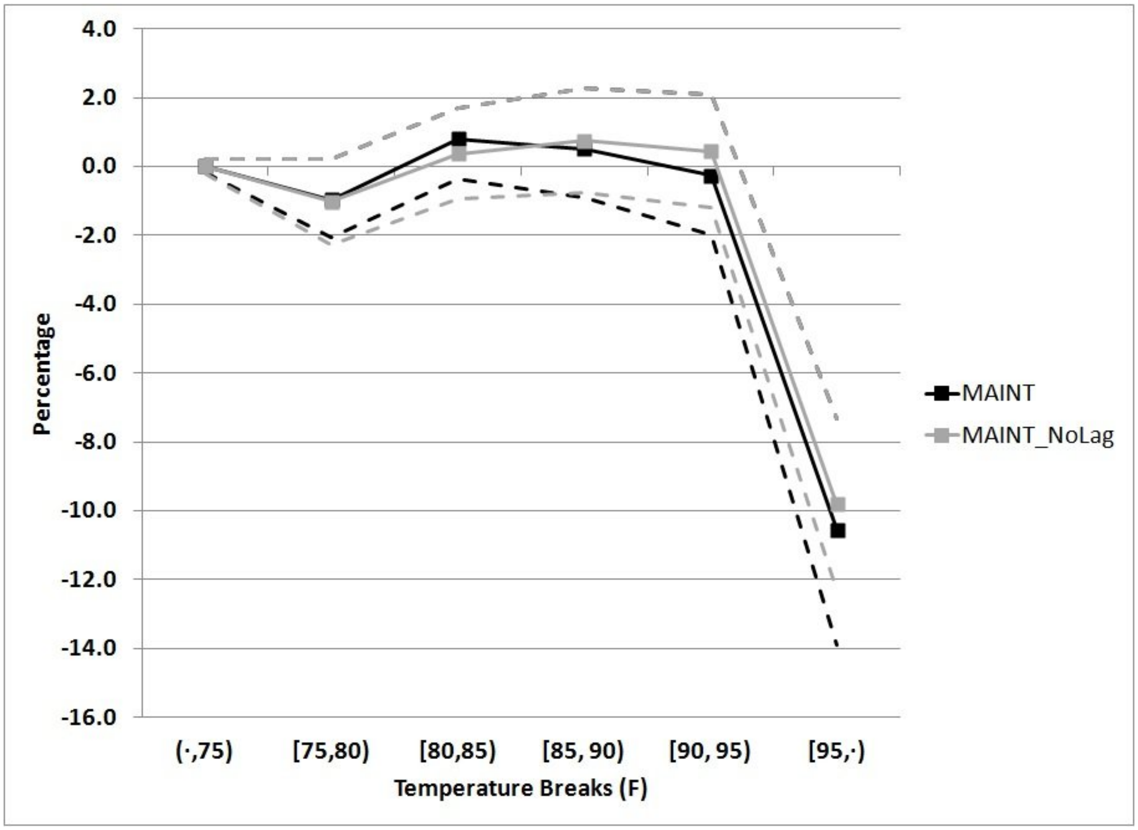
5.C Robustness Checks

This section conducts a series of robustness check to determine the sensitivity of the basic results.

5.C.1 Removing Lag Variable

Adding the variable *LagL100* creates dependence between observations and might result in correlated error terms that bias the estimates. For this reason, the model is rerun removing the lag variable from equation (5). Figure 12 plots the results for the *SUMMER* × *MAX* × *EWG* estimates for the *MAINT* dependent variable, where the black line reports the baseline estimate as in figure 11, while the grey line reports the estimates from the model without the lag variable (and the dashed lines indicated the 95% confidence interval). The figure shows no statistical difference between the baseline model and the model without the lag variable.

Figure 12: ***SUMMER* × *MAX* × *EWG* for each Temperature Group with Dependent Variable *MAINT* without *LagL100***



5.C.2 Adding Unit-Level Characteristics

The baseline model already clusters at the plant level, but it is useful to check if adding observable unit-level characteristics significantly changes the results.[20] Table 7 describes the additional control variables added to the baseline model (as originally detailed in section 3). Importantly, this model adds dummy variables for NGU ownership, in case one company is more efficient at maintaining its NGUs than another.[21] As shown in Figure 13, adding these unit-level controls to the baseline model does not significantly change results.

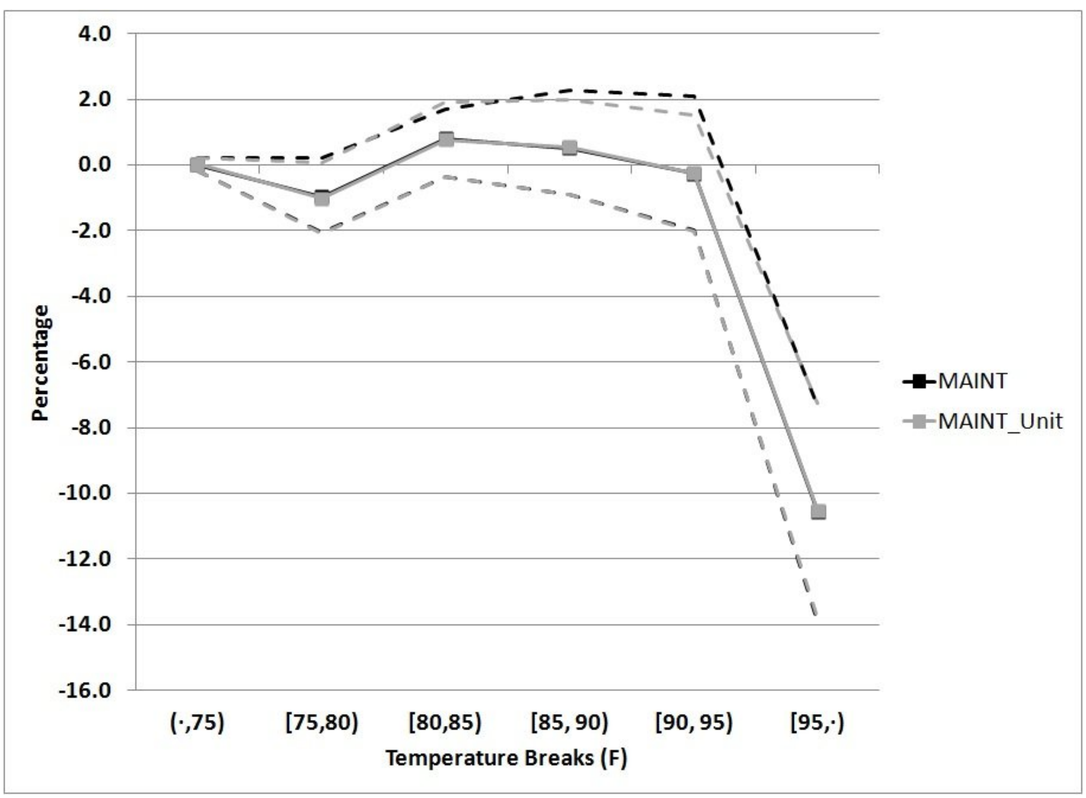
[20] In a study just focusing on U.S. NGUs, Rothwell (1990) decomposes capacity factors into utilization rates and service factors, and identifies the relationship between productivity and observed NGU characteristics.

[21] Lester and McCabe (1993) find that learning-by-doing is an important factor in NGU performance, and it might be the case the knowledge about how to efficiently run an NGU is transferred to all NGU within a company.

Table 7: List of Additional Unit-Level Controls

Name	Description
Consecutive *L100* Days Count	The running count (e.g. 1,2,3,…), and running count squared, of the number of days that the variable *L100* equals 1.
Age	Age and age squared of each NGU as of 2008.
Capacity	Capacity (MW) and capacity squared of each NGU as of 2008.
NRC Region	Dummy variables controlling for the four Nuclear Regulatory Commission regions (see figure 3).
Reactor Type	Dummy variable for reactor type.
Containment Type	Dummy variables for reactor containment configuration.
Supplier	Dummy variables for reactor supplier.
Reactor Design	Dummy variables for reactor design.
Architect	Dummy variables for NGU architect.
Constructor	Dummy variables for NGU construction firm.
Same Architect & Constructor	Dummy equal to 1 if a NGU has the same architect and construction firm.
Construction Permit Date	Date of NGU construction permit.
Time from 1st Construction Permit	Length (in years) between a NGU's construction permit and the first U.S. NGU construction permit.
Construction Length	Length (in years) of NGU construction measured from date of construction permit until beginning of commercial operation.
Start After TMI	Dummy variable indicating if NGU began operation after the Three Mile Island reactor meltdown.
Operating License Expiration Date	Date of NGU operating license expiration from NRC.
Firms	Dummy variables controlling for the NGU ownership from EIA Form-923.

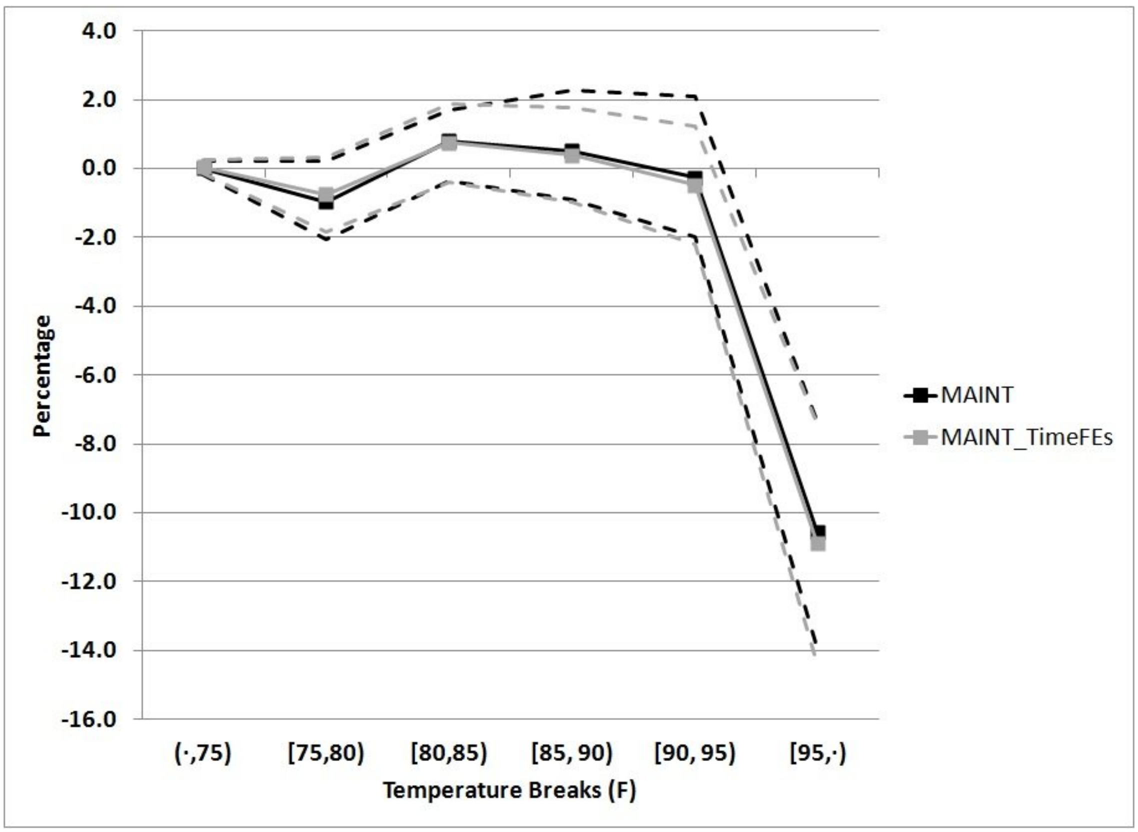
Figure 13: *SUMMER* × *MAX* × *EWG* for each Temperature Group with Dependent Variable *MAINT* adding Unit-Level Characteristics



5.C.3 Time Fixed-Effects

Here, year-month fixed-effects along with day of the week fixed-effects are added to the baseline model. Using finely delineated time fixed-effects is similar to estimating a time-trend and may even be call a "non-parametric time-trend". Again, as Figure 14 shows, adding these time fixed-effects does not significantly change the model results. Interestingly, in level terms, planned maintenance is lower on weekend days than weekdays.

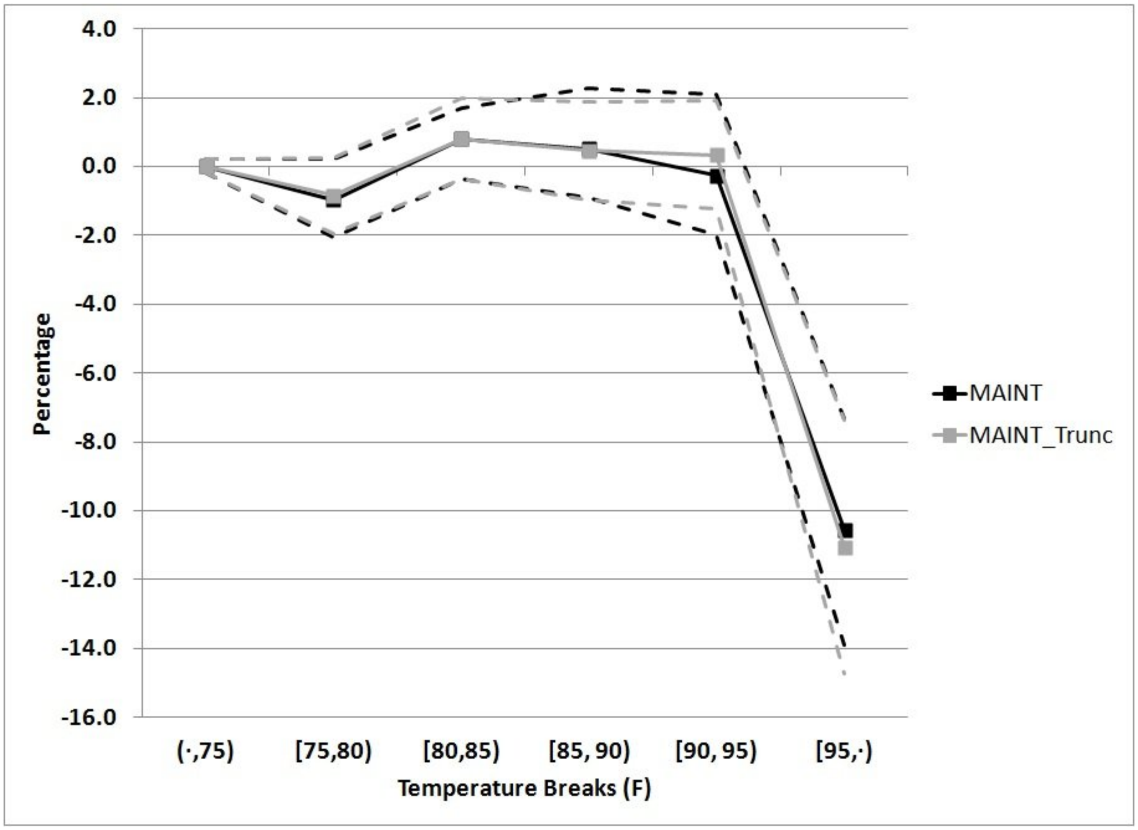
Figure 14: $\boldsymbol{SUMMER \times MAX \times EWG}$ **for each Temperature Group with Dependent Variable *MAINT* adding Time Fixed-Effects**



5.C.4 Truncated Dataset

The final robustness check removes the two plants (five units) with high temperature group 6 representation (see figure 10). It is a concern that these five units with their large weight in group 6 are biasing the results. After removing these units and rerunning the baseline model with the truncated dataset does not change the estimate significantly (see figure 15).

Figure 15: *SUMMER* × *MAX* × *EWG* for each Temperature Group with Dependent Variable *MAINT* using Truncated Dataset



6 Discussion and Conclusion

This paper finds statistically significant maintenance-allocation efficiency gains. I then calculate the annual dollar value of the maintenance-allocation efficiency gains to be $5.5 million dollars per year (if all U.S. NGU were in wholesale markets compared to all under regulated pricing). However, this dollar value for the total maintenance-allocation efficiency gains may be low for at least two reasons. First, fuel costs are not included in the cost calculation, and increasing fossil-fuel prices may lead to a larger difference in operating costs between NUGs and peaker units. Second, environmental benefits are not included either, and some pollutants on high-temperature days cause more damages than low-temperature days. Since peaker units are fossil-fuel fired, their environmental impacts might be an important real cost.

Finally, I acknowledge three issues that may lead to concerns about the results. First, the variables generated from the PRSPs may not accurately capture actual operations at the NGUs. For instance, I assumed that all outages categorized as *OTHER* were planned outages since they did not fall under *SCRAM* or *FUEL* categories, and that may not be an accurate assumption. Second, the binary treatment variable *EWG* may not accurately reflect the true and complete state of electricity price deregulation at the wholesale level for each NGU. Third, the result found in this paper is specific to NGUs and may not apply to all EGUs, as mentioned above. It is unclear how the maintenance-allocation efficiency gains from marginal pricing accrue to other types of generating units that do not satisfy the full-dispatch assumption needed for identification. However, it seemly likely that maintenance-allocation efficiency gains accrue at all types of electricity generating units in wholesale electricity markets.

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Appendix A: Additional Data

Table A-1: List U.S. Nuclear Generating Units in 2009

Reactor Name	State	Type	2009 Summer Capacity Net MW	Construction Start	Commercial Operation
Arkansas Nuclear-1	AR	PWR	842	10/1/1968	12/19/1974
Arkansas Nuclear-2	AR	PWR	993	7/1/1971	3/26/1980
Beaver Valley-1	PA	PWR	892	6/1/1970	10/1/1976
Beaver Valley-2	PA	PWR	885	5/1/1974	11/17/1987
Braidwood-1	IL	PWR	1,178	8/1/1975	7/29/1988
Braidwood-2	IL	PWR	1,152	8/1/1975	10/17/1988
Browns Ferry-1	AL	BWR	1,066	5/1/1967	8/1/1974
Browns Ferry-2	AL	BWR	1,104	5/1/1967	3/1/1975
Browns Ferry-3	AL	BWR	1,105	7/1/1968	3/1/1977
Brunswick-1	NC	BWR	938	9/1/1969	3/18/1977
Brunswick-2	NC	BWR	920	9/1/1969	11/3/1975
Byron-1	IL	PWR	1,164	4/1/1975	9/16/1985
Byron-2	IL	PWR	1,136	4/1/1975	8/2/1987
Callaway-1	MO	PWR	1,190	9/1/1975	12/19/1984
Calvert Cliffs-1	MD	PWR	855	6/1/1968	5/8/1975
Calvert Cliffs-2	MD	PWR	850	6/1/1968	4/1/1977
Catawba-1	SC	PWR	1,129	5/1/1974	6/29/1985
Catawba-2	SC	PWR	1,129	5/1/1974	8/19/1986
Clinton-1	IL	BWR	1,065	10/1/1975	11/24/1987
Columbia-2*	WA	BWR	1,131	8/1/1972	12/13/1984
Comanche Peak-1	TX	PWR	1,209	10/1/1974	8/13/1990
Comanche Peak-2	TX	PWR	1,158	10/1/1974	8/3/1993
Cooper	NE	BWR	774	6/1/1968	7/1/1974
Crystal River-3	FL	PWR	860	6/1/1967	3/13/1977
Davis Besse-1	OH	PWR	894	9/1/1970	7/31/1978
Diablo Canyon-1	CA	PWR	1,122	8/1/1968	5/7/1985
Diablo Canyon-2	CA	PWR	1,118	12/1/1970	3/13/1986
Donald Cook-1	MI	PWR	1,009	3/1/1969	8/28/1975
Donald Cook-2	MI	PWR	1,060	3/1/1969	7/1/1978
Dresden-2	IL	BWR	867	1/1/1966	6/9/1970
Dresden-3	IL	BWR	867	10/1/1966	11/16/1971
Duane Arnold-1	IA	BWR	601	6/1/1970	2/1/1975
Enrico Fermi-2	MI	BWR	1,106	5/1/1969	1/23/1988
Farley-1	AL	PWR	851	10/1/1970	12/1/1977
Farley-2	AL	PWR	860	10/1/1970	7/30/1981
Fitzpatrick	NY	BWR	855	9/1/1968	7/28/1975
Fort Calhoun-1	NE	PWR	478	6/1/1968	9/26/1973
Grand Gulf-1	MS	BWR	1,251	5/1/1974	7/1/1985
H.B. Robinson-2	SC	PWR	724	4/1/1967	3/7/1971

Hatch-1	GA	BWR	876	9/1/1968	12/31/1975
Hatch-2	GA	BWR	883	2/1/1972	9/5/1979
Hope Creek-1	NJ	BWR	1,161	3/1/1976	12/20/1986
Indian Point-2	NY	PWR	1,022	10/1/1966	8/1/1974
Indian Point-3	NY	PWR	1,040	11/1/1968	8/30/1976
Kewaunee	WI	PWR	556	8/1/1968	6/16/1974
LaSalle-1	IL	BWR	1,118	9/1/1973	1/1/1984
LaSalle-2	IL	BWR	1,120	10/1/1973	10/19/1984
Limerick-1	PA	BWR	1,130	4/1/1970	2/1/1986
Limerick-2	PA	BWR	1,134	4/1/1970	1/8/1990
McGuire-1	NC	PWR	1,100	4/1/1971	12/1/1981
McGuire-2	NC	PWR	1,100	4/1/1971	3/1/1984
Millstone-2	CT	PWR	869	11/1/1969	12/26/1975
Millstone-3	CT	PWR	1,233	5/1/1974	4/23/1986
Monticello	MN	BWR	572	6/1/1967	6/30/1971
Nine Mile Point-1	NY	BWR	621	4/1/1965	12/1/1969
Nine Mile Point-2	NY	BWR	1,143	8/1/1975	3/11/1988
North Anna-1	VA	PWR	903	2/1/1971	6/6/1978
North Anna-2	VA	PWR	903	11/1/1970	12/14/1980
Oconee-1	SC	PWR	846	11/1/1967	7/15/1973
Oconee-2	SC	PWR	846	11/1/1967	9/9/1974
Oconee-3	SC	PWR	846	11/1/1967	12/16/1974
Oyster Creek	NJ	BWR	615	1/1/1964	12/1/1969
Palisades	MI	PWR	778	2/1/1967	12/31/1971
Palo Verde-1	AZ	PWR	1,311	5/1/1976	1/28/1986
Palo Verde-2	AZ	PWR	1,314	6/1/1976	9/19/1986
Palo Verde-3	AZ	PWR	1,317	6/1/1976	1/8/1988
Peach Bottom-2	PA	BWR	1,122	1/1/1968	7/5/1974
Peach Bottom-3	PA	BWR	1,112	1/1/1968	12/23/1974
Perry-1	OH	BWR	1,240	10/1/1974	11/18/1987
Pilgrim-1	MA	BWR	685	8/1/1968	12/1/1972
Point Beach-1	WI	PWR	512	7/1/1967	12/21/1970
Point Beach-2	WI	PWR	515	7/1/1968	10/1/1972
Prairie Island-1	MN	PWR	551	5/1/1968	12/16/1973
Prairie Island-2	MN	PWR	545	5/1/1969	12/21/1974
Quad Cities-1	IL	BWR	882	2/1/1967	2/18/1973
Quad Cities-2	IL	BWR	892	2/1/1967	3/10/1973
R.E. Ginna	NY	PWR	581	4/1/1966	7/1/1970
River Bend-1	LA	BWR	974	3/1/1977	6/16/1986
Salem-1	NJ	PWR	1,174	1/1/1968	6/30/1977
Salem-2	NJ	PWR	1,158	1/1/1968	10/13/1981
San Onofre-2	CA	PWR	1,070	3/1/1974	8/8/1983
San Onofre-3	CA	PWR	1,080	3/1/1974	4/1/1984
Seabrook-1	NH	PWR	1,247	7/1/1976	8/19/1990
Sequoyah-1	TN	PWR	1,152	5/1/1970	7/1/1981

Sequoyah-2	TN	PWR	1,126	5/1/1970	6/1/1982
Shearon Harris-1	NC	PWR	900	1/1/1974	5/2/1987
South Texas-1	TX	PWR	1,280	9/1/1975	8/25/1988
South Texas-2	TX	PWR	1,280	9/1/1975	6/19/1989
St. Lucie-1	FL	PWR	839	7/1/1970	12/21/1976
St. Lucie-2	FL	PWR	839	6/1/1976	8/8/1983
Surry-1	VA	PWR	799	6/1/1968	12/22/1972
Surry-2	VA	PWR	799	6/1/1968	5/1/1973
Susquehanna-1	PA	BWR	1,185	11/1/1973	6/8/1983
Susquehanna-2	PA	BWR	1,190	11/1/1973	2/12/1985
Three Mile Island-1	PA	PWR	805	5/1/1968	9/2/1974
Turkey Point-3	FL	PWR	693	4/1/1967	12/14/1972
Turkey Point-4	FL	PWR	693	4/1/1967	9/7/1973
Vermont Yankee	VT	BWR	620	12/1/1967	11/30/1972
Virgil C. Summer- 1	SC	PWR	966	3/1/1973	1/1/1984
Vogtle-1	GA	PWR	1,150	8/1/1976	6/1/1987
Vogtle-2	GA	PWR	1,152	8/1/1976	5/20/1989
Waterford-3	LA	PWR	1,168	11/1/1974	9/24/1985
Watts Bar-1	TN	PWR	1,123	12/1/1972	5/27/1996
Wolf Creek	KS	PWR	1,160	1/1/1977	9/3/1985
Total			**101,004**		

Summer Capacity (Net): The maximum output (excluding electricity used for station's internal operations, expressed in Megawatts (electricity). Note that nuclear power can also be expressed in Megawatts (thermal).

PWR = Pressurized light Water Reactor

BWR = Boiling Water Reactor

(Source: Nuclear Regulatory Commission via U.S. Energy Information Agency)

Figure A-1: Random Sample of Raw NRC Power Reactor Status Reports from November 1, 2008

Unit	Power	Down	Reason or Comment	Change in report (*)	Number of Scrams (#)
Browns Ferry 1	0	10/25/2008	ONE COOLING TOWER TRANSFORMER OOS; REFUELING OUTAGE		
Browns Ferry 2	100		ONE COOLING TOWER TRANSFORMER OOS		
Browns Ferry 3	100		ONE COOLING TOWER TRANSFORMER OOS		
Brunswick 1	100				
Brunswick 2	70		ROD WORTH TESTING	*	
Catawba 1	100				
Catawba 2	100				
Crystal River 3	100				
Farley 1	100				
Farley 2	0	10/19/2008	REFUELING OUTAGE - DEFUELED		
Harris 1	100				
Hatch 1	100				
Hatch 2	100				
McGuire 1	0	09/15/2008	MANUAL TRIP ROD CONTROL MALFUNCTION. SEE EN #44618.	*	1
McGuire 2	100			*	
North Anna 1	100				
North Anna 2	0	10/29/2008	MAINTENANCE OUTAGE		

(Source: Nuclear Regulatory Commission; Downloaded Download December 2010)

Table A-2: Exempt Wholesale Generator (EWG) Status for U.S. Nuclear Generating Units 2001-2008

Plant	Unit	State	2001	2002	2003	2004	2005	2006	2007	2008
Browns Ferry	1	AL	N	N	N	N	N	N	N	N
Browns Ferry	2	AL	N	N	N	N	N	N	N	N
Browns Ferry	3	AL	N	N	N	N	N	N	N	N
Clinton	1	IL	N	N	N	N	N	N	N	N
Wolf Creek	1	KS	N	N	N	N	N	N	N	N
San Onofre	2	CA	N	N	N	N	N	N	N	N
San Onofre	3	CA	N	N	N	N	N	N	N	N
Columbia	2	WA	N	N	N	N	N	N	N	N
Millstone	2	CT	N	N	N	N	N	N	N	N
Millstone	3	CT	N	N	N	N	N	N	N	N
Turkey Point	3	FL	N	N	N	N	N	N	N	N
Turkey Point	4	FL	N	N	N	N	N	N	N	N
Crystal River	3	FL	N	N	N	N	N	N	N	N
Vogtle	1	GA	N	N	N	N	N	N	N	N
Vogtle	2	GA	N	N	N	N	N	N	N	N
Dresden	2	IL	N	N	N	N	N	N	N	N
Dresden	3	IL	N	N	N	N	N	N	N	N
Quad Cities	1	IL	N	N	N	N	N	N	N	N
Quad Cities	2	IL	N	N	N	N	N	N	N	N
Duane Arnold	1	IA	N	N	N	N	N	N	N	N
Pilgrim	1	MA	Y	Y	Y	Y	Y	Y	Y	Y
Palisades	1	MI	N	N	N	N	N	N	Y	Y
Fermi	2	MI	N	N	N	N	N	N	N	N
Monticello	1	MN	N	N	N	N	N	N	N	N
Prairie Island	1	MN	N	N	N	N	N	N	N	N
Prairie Island	2	MN	N	N	N	N	N	N	N	N
Fort Calhoun	1	NE	N	N	N	N	N	N	N	N
Oyster Creek	1	NJ	Y	N	N	N	N	N	N	N
Salem	1	NJ	Y	Y	Y	Y	Y	Y	Y	Y
Salem	2	NJ	Y	Y	Y	Y	Y	Y	Y	Y
Indian Point 2	2	NY	Y	Y	Y	Y	Y	Y	Y	Y
Nine Mile Point	1	NY	Y	Y	Y	Y	Y	Y	Y	Y
Nine Mile Point	2	NY	Y	Y	Y	Y	Y	Y	Y	Y
Peach Bottom	2	PA	N	N	N	N	N	N	N	N
Peach Bottom	3	PA	N	N	N	N	N	N	N	N
H B Robinson	2	SC	N	N	N	N	N	N	N	N
Oconee	1	SC	N	N	N	N	N	N	N	N
Oconee	2	SC	N	N	N	N	N	N	N	N
Oconee	3	SC	N	N	N	N	N	N	N	N
Vermont Yankee	1	VT	N	N	Y	Y	Y	Y	Y	Y
Surry	1	VA	N	N	N	N	N	N	N	N
Surry	2	VA	N	N	N	N	N	N	N	N
Point Beach	1	WI	N	N	N	N	N	N	N	N

Point Beach	2	WI	N	N	N	N	N	N	N	N
Waterford 3	3	LA	N	N	N	N	N	N	N	N
Donald C Cook	1	MI	N	N	N	N	N	N	N	N
Donald C Cook	2	MI	N	N	N	N	N	N	N	N
Joseph M Farley	1	AL	N	N	N	N	N	N	N	N
Joseph M Farley	2	AL	N	N	N	N	N	N	N	N
Palo Verde	1	AZ	N	N	N	N	N	N	N	N
Palo Verde	2	AZ	N	N	N	N	N	N	N	N
Palo Verde	3	AZ	N	N	N	N	N	N	N	N
Calvert Cliffs	1	MD	Y	Y	Y	Y	Y	Y	Y	Y
Calvert Cliffs	2	MD	Y	Y	Y	Y	Y	Y	Y	Y
Brunswick	1	NC	N	N	N	N	N	N	N	N
Brunswick	2	NC	N	N	N	N	N	N	N	N
Harris	1	NC	N	N	N	N	N	N	N	N
Perry	1	OH	N	N	N	N	N	N	N	N
Braidwood	1	IL	N	N	N	N	N	N	N	N
Braidwood	2	IL	N	N	N	N	N	N	N	N
Byron	1	IL	N	N	N	N	N	N	N	N
Byron	2	IL	N	N	N	N	N	N	N	N
LaSalle	1	IL	N	N	N	N	N	N	N	N
LaSalle	2	IL	N	N	N	N	N	N	N	N
Catawba	1	SC	N	N	N	N	N	N	N	N
Catawba	2	SC	N	N	N	N	N	N	N	N
McGuire	1	NC	N	N	N	N	N	N	N	N
McGuire	2	NC	N	N	N	N	N	N	N	N
Beaver Valley	1	PA	N	N	N	N	N	N	N	N
Beaver Valley	2	PA	N	N	N	N	N	N	N	N
St Lucie	1	FL	N	N	N	N	N	N	N	N
St Lucie	2	FL	N	N	N	N	N	N	N	N
Edwin I Hatch	1	GA	N	N	N	N	N	N	N	N
Edwin I Hatch	2	GA	N	N	N	N	N	N	N	N
Grand Gulf	1	MS	N	N	N	N	N	N	N	N
Diablo Canyon	1	CA	N	N	N	N	N	N	N	N
Diablo Canyon	2	CA	N	N	N	N	N	N	N	N
Susquehanna	1	PA	Y	N	Y	Y	Y	Y	Y	Y
Susquehanna	2	PA	Y	Y	Y	Y	Y	Y	Y	Y
Limerick	1	PA	N	N	N	N	N	N	N	N
Limerick	2	PA	N	N	N	N	N	N	N	N
James A Fitzpatrick	1	NY	Y	Y	Y	Y	Y	Y	Y	Y
Seabrook	1	NH	N	N	Y	Y	Y	Y	Y	Y
Hope Creek	1	NJ	Y	Y	Y	Y	Y	Y	Y	Y
R. E. Ginna	1	NY	N	N	N	Y	Y	Y	Y	Y
V C Summer	1	SC	N	N	N	N	N	N	N	N
Comanche Peak	1	TX	N	N	N	N	N	N	N	N
Comanche Peak	2	TX	N	N	N	N	N	N	N	N
Davis Besse	1	OH	N	N	N	N	N	N	N	N
Sequoyah	1	TN	N	N	N	N	N	N	N	N

Sequoyah	2	TN	N	N	N	N	N	N	N	N
Callaway	1	MO	N	N	N	N	N	N	N	N
North Anna	1	VA	N	N	N	N	N	N	N	N
North Anna	2	VA	N	N	N	N	N	N	N	N
South Texas Project	1	TX	N	N	N	N	N	N	N	N
South Texas Project	2	TX	N	N	N	N	N	N	N	N
River Bend	1	LA	N	N	N	N	N	N	N	N
Watts Bar	1	TN	N	N	N	N	N	N	N	N
Three Mile Island	1	PA	Y	Y	Y	Y	Y	Y	N	N
Kewaunee	1	WI	N	N	N	N	Y	Y	Y	Y
Cooper	1	NE	N	N	N	N	N	N	N	N
Arkansas Nuclear One	1	AR	N	N	N	N	N	N	N	N
Arkansas Nuclear One	2	AR	N	N	N	N	N	N	N	N
Indian Point 3	3	NY	Y	Y	Y	Y	Y	Y	Y	Y

[Note: Grey colored cells indicate missing data filled-in by author.]
(Source: U.S. Energy Information Agency Form-860)