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A Hazard Rate Analysis of Mirant's Generating Plant Outages in California (Jan-04)

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A HAZARD RATE ANALYSIS OF MIRANT'S GENERATING PLANT OUTAGES IN CALIFORNIA

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Abstract A model of generator withholding is critical for analyses of market power. The California electricity market crisis of 2000-2001 saw increased utilization of fossil fuel plants. The stressed conditions could have affected normal outage rates. A hazard rate analysis applied to the Mirant generating plants indicates that higher utilization should increase outage rates. The predicted crisis outage rates should have been higher than the historical average. Actual outage rates were significantly lower than would be predicted based on pre-crisis behavior.

Introduction

The California electricity market crisis of 2000-2001 and its reverberations produced long-term effects throughout the world. High electricity prices and potentially large transfers of wealth precipitated extensive inquiries into the immediate causes of the crisis. Given the complexity of the electricity system, the data requirements needed to analyze the causes of the high prices are substantial and often neither the data nor the software systems required are publicly available. A central focus of many analyses has been on the exercise of market power by generators withholding supply. Absent withholding, high prices could be explained as the result of shortage conditions during which price rose until demand was reduced (such as by the closing of aluminum plants in the Northwest). Hence, a model of generator withholding is critical for most analyses of market power.

It is common to distinguish between economic withholding and physical withholding. Economic withholding refers to offering generation for dispatch at high prices that result in underutilization of otherwise marginal or infra-marginal generation. Physical withholding refers to a failure to offer otherwise marginal or infra-marginal generation for dispatch at any price. In the case of electricity, it is often assumed that a simple mechanism for physical withholding might be to declare a maintenance outage or an equipment failure that results in an artificial "forced" outage.

While the validity of an individual outage might be difficult for regulators to evaluate, a pattern of unusual maintenance or forced outages would lend itself to statistical analysis. The present paper includes a hazard rate analysis of outages applied to a set of plants owned by

[1] See endnote for affiliations.

Mirant during the period of the California crisis.[2] The data cover the period 1994 to 2001. Mirant acquired the plants from Pacific Gas & Electric (PG&E) corporation effective April 1, 1999, and also acquired five years of historical outage and output data for these units under PG&E operation going back to April 1, 1994.

Market Power and Market Prices

The nature of the electricity system and the limited ability to store power lead most analyses of the California crisis to focus on activities in the physical or spot market. Under the stress of increased demand or reduced supply, competitive prices could increase due to the effects of scarcity. In essence, the simple comparative statics of the monopoly model provide the analytical framework for the analysis of market power.[3] Faced with a downward sloping residual demand curve, each supplier may see an incentive to increase prices by withdrawing supply in order to profit from higher prices on infra-marginal output. The critical difference between competitive and non-competitive outcomes is not the price level but the withdrawal of marginal or infra-marginal supply, reducing supply below the efficient level.

Broadly speaking, there have been two primary approaches to the analysis of the exercise of market power by generators. Examination of the behavior of individual generators could identify gaps between actual and potential output that could reflect economic or physical withholding and thus the exercise of market power.[4] Another approach is to attempt to identify the exercise of market power through a comparison of actual market outcomes to counterfactual simulations of price and output with no strategic behavior.[5]

Both approaches face a difficulty in characterizing the expected behavior of individual generators operating within the overall transmission and dispatch system under stressed conditions. In essence, the analysis of market power in the California context faces the task of separating the effects of shortage conditions arising from reduced hydro generation, nuclear outages, inefficient market design, and environmental limitations, about which there is little dispute, from the effects of the exercise of market power. The impacts of each could be quite large. Borenstein et al. estimate that 50 percent of total electricity expenditures in summer 2000

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2 The authors obtained access to these data as consultants to Mirant in the proceedings before the Federal Energy Regulatory Commission under Docket Nos. EL00-95-075 and EL00-98-063 addressing the California electricity markets. Initially the proceedings were confidential, but Mirant placed its submissions in the public record.

3 For example, see Figure 6, Severin Borenstein, James B. Bushnell, and Frank A. Wolak, "Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market," *The American Economic Review*, Vol. 92, No. 5, December 2002, p. 1397.

4 Paul L. Joskow and Edward Kahn, "A Quantitative Analysis of Pricing in California's Wholesale Electricity Market During Summer 2000," *The Energy Journal*, Vol. 23, No. 4, 2002, Section 6.

5 Prominent examples of the counterfactual simulations for California include: Severin Borenstein, James B. Bushnell, and Frank A. Wolak, "Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market," *The American Economic Review*, Vol. 92, No. 5, December 2002, pp. 1376-1405. Paul L. Joskow and Edward Kahn, "A Quantitative Analysis of Pricing in California's Wholesale Electricity Market During Summer 2000," *The Energy Journal*, Vol. 23, No. 4, 2002, Sections 3-4.

could be attributed to market power.[6] Other tests of the counterfactual simulations yield results implying that the exercise of market power had little or no impact on electricity prices.[7]

In the detailed examination of the behavior of individual plants, application of environmental restrictions, ramping limits, reserve requirements and so on can have material effects on the available capacity of generators. What looks like withholding may have an alternative explanation, and plant specific investigations have yet to produce clear evidence of significant physical withholding.[8] The absence of a "smoking gun" may suggest no material withholding occurred. Another view is that it is inherently difficult to find evidence of physical withholding in the form of false declarations of generation outages or deratings. For example, consider the comments of the market monitor of the California Independent System Operator (CAISO):

> "The events of the past six months and the extremely high forced outages rates that have occurred in the California market and accompanying plant inspections by the California Public Utilities Commission (CPUC) and Federal Energy Regulatory Commission (FERC) Staff have demonstrated the following very important fact about competitive electricity market: it is impossible to determine whether or not a declared forced outage is in fact an actual forced outage. It is impossible to determine whether a declared forced outage occurs because the plant is actually unable to operate or because this action increases the generation unit owner's profits. Electricity generating units are extremely complex pieces of machinery and enormous public safety and public health hazards are associated with operating them if they are not in proper working order. Consequently, even an experienced power-systems engineer brought in to inspect the plant would be unable to determine if a plant that had been declared unable to run could in fact run. Clearly, there is a considerable amount of operator judgement involved in determining whether a power plant should run; nonetheless, we clearly should defer to the judgement of the plant operator for this decision.
>
> A useful analogy to this problem comes from the labor market. We can think of sick days as the analogue to forced outages. It is very difficult for an employee's boss to tell whether the reason the employee has called in sick is because he is truly unable to work or he would prefer to spend a day relaxing at home. The boss could come to the employee's house with a doctor and have the doctor examine the employee. However, given that the human body is not

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6 Severin Borenstein, James B. Bushnell, and Frank A. Wolak, "Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market," *The American Economic Review*, Vol. 92, No. 5, December 2002, p. 1377.

7 Scott M. Harvey and William W. Hogan, "Market Power and Market Simulations," Center for Business and Government, Harvard University, July 16, 2002 (available at www.whogan.com).

8 For example, on examination of the initial investigation by the California Public Utility Commission, the FERC Staff concluded that "[t]here is no evidence that any of the generators withheld any material amounts of available power *during the hours of the firm service interruptions*." Federal Energy Regulatory Commission, "Staff's Review of California Public Utility Commission's September 17, 2002, Investigative Report On Wholesale Electric Generation," March 26, 2003. p. 4, (emphasis in original).

completely understood by the medical profession, the employee could still fabricate some disease unknown to the doctor that prevents the employee from working. The employee's boss recognizes this problem and therefore refrains from questioning the veracity of an employee's claim to a sick day."[9]

The analogy may be apt for an isolated incident based on unusual circumstances. But system operators who oversee transmission and dispatch are more like doctors themselves, and they are familiar with the patients. Therefore, a pattern of abuse should be easier to identify. And even analysts more distant from system operations should be able to conduct statistical studies of outage behavior.

The counterfactual simulations complement the analysis of individual cases and illustrate the importance of accurate characterization of expected outages. The importance of the outage assumptions can be best seen through a simple sensitivity test with the ubiquitous "single stack" simulation model.[10] The basic model for competitive spot market supply "stacks" the available plants from lowest to highest cost. Taking each hour separately, and given any level of demand, the resulting competitive price follows from the supply curve at that level of demand. This counterfactual estimate of the competitive price is then compared with the observed price in the market.

One reason why counter-factual simulations based on a single stack optimization model yield problematic predictions of the competitive price level under stressed conditions follows from the tendency of the supply curve to rise rapidly at high levels of output near the capacity of the system. In this range, a small level of supply withholding to exercise market power could produce a large price increase. Unfortunately, this same feature means that small errors in the supply included in the single stack model could produce large changes in the simulated price in this same range.

Figure 1 depicts supply curves for California thermal capacity for an illustrative case.[11] The details of the particular case are not important for the illustration. The total nameplate capacity of the thermal plants in California is reasonably well-known. However, the actual ability of this capacity to generate electricity can depend on factors such as ambient air temperature, tide levels for cooling water, river and bay cooling water temperatures, and the amount of sea life clogging water inlet pipes. In addition, not all the nameplate capacity is available at any time, with some out for regular maintenance or unscheduled forced outages or

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9 Frank A. Wolak, Chairman, Market Surveillance Committee (MSC) of the California Independent System Operator (ISO), "Proposed Market Monitoring Plan for California Electricity Market, February 6, 2001, p. 14.

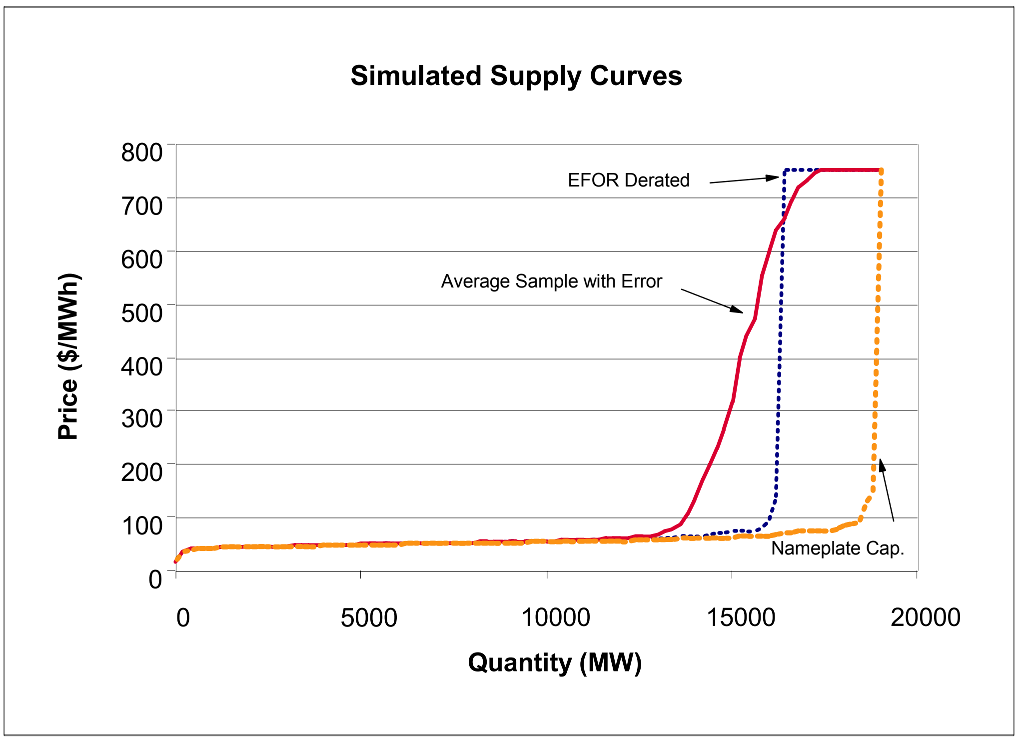
10 Scott M. Harvey and William W. Hogan, "Market Power and Market Simulations," Center for Business and Government, Harvard University, July 16, 2002 (available at www.whogan.com).

11 The emphasis is on the shape of the curve rather than the details of the particular case. For details, see Scott M. Harvey and William W. Hogan, "Market Power and Market Simulations," Center for Business and Government, Harvard University, July 16, 2002. For similar depictions of the single stack model see Figure 1 in Severin Borenstein, James B. Bushnell, and Frank A. Wolak, "Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market," *The American Economic Review*, Vol. 92, No. 5, December 2002, p. 1385; Figure 1, Paul L. Joskow and Edward Kahn, "A Quantitative Analysis of Pricing in California's Wholesale Electricity Market During Summer 2000," *The Energy Journal*, Vol. 23, No. 4, 2002, p. 7.

deratings arising from mechanical operating problems, rather than the environmental factors noted above. Simulation models such as those applied by Joskow and Kahn attempt to take account of the impact of outages and deratings on the supply curve by reducing the name plate capacity to reflect the impact of equivalent forced outage rates (EFOR) to derive a derated supply curve that is used in the simulation. Setting aside the difficulties in estimating costs and characterizing other constraints on real operations, suppose that the assumed outage rate in the static, single-price model that ignores dynamics, environmental limitations, greater stress on the plants, and so on, understates the chance that an individual plant is unavailable in any hour by 5 percentage points. The impact of such an error can be seen by repeating the simulation with a 5 percent increase in the assumed outage rate.

Figure 1

Comparison of Static Thermal Electricity Supply Curve, California June 2000



Using this higher effective outage rate, a Monte Carlo sampling produces an average supply curve subject to a $750 price cap. The result of comparing prices from the simulation with the higher outage rate to "competitive" prices produced by the simulation using the lower outage rate has the same properties often described as indicative of the exercise of market power. In particular, the markup between the price curve based on the higher outage rates and the "competitive" derated supply curve is virtually zero at low load levels, and the markup rises rapidly as load approaches the maximum of the derated supply curve.[12] Using a dispatch load profile from a June 2000 simulation, the average price using the higher outage rate is approximately $105 per MWh versus the "competitive" derated simulation of $59, for an apparent markup of 44 percent. However, in this illustration we know that this difference is not a result of the exercise of market power. It is the result of assumed competitive behavior but with a 5 percent difference in the real availability of plants compared to the static ideal. Determining that this markup arises from an exercise of market power and not from such an error in the model requires controlling for errors in the model well beneath this 5 percent level. As we see below, this fidelity of the model would be hard to achieve.

This example illustrates a general feature of simulation based market analyses. They produce a finding that the simulated price is different from the actual price, but they do not identify the reason for the difference, i.e., whether the price difference is a result of inaccurate assumptions (including the outage rate), good or bad luck in real-world outcomes, the inability of a simulation to model the chaos and uncertainty of real-world real-time operations, failure to model market institutions (such as the inefficient design of the California electricity market) or the exercise of market power. Thus, it has been noted that "[a] potential drawback of the market-level approach is that it captures all inefficiencies in the market, some of which may not be due to market power."[13] Further, it is difficult to separate the effect of errors in the counterfactual model from the apparent exercise of market power without undertaking further analyses. As one of its critical factors, application of the simulation model requires some baseline assumption about the counterfactual outage rates.

The typical application of the simulation models has been careful to recognize that outage rates are potentially subject to strategic manipulation: "We did not adjust the output of generation units for actual outages, because scheduling and duration of planned outages for maintenance and other activities is itself a strategic decision."[14] A typical approach has been to replace the actual outage rates, potentially influenced by strategic behavior, with a measure of

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12 The Joskow-Kahn analysis uses a derated supply curve. The Borenstein, Bushnell, and Wolak model applies a Monte Carlo simulation. The Monte Carlo simulation is important in showing the dispersion in prices relative to the derated supply curve. Borenstein et al. argue further that the Monte Carlo method is necessary because of the convexity of the competitive supply curve (BB&W, *AER*, p. 1385). However, as seen in the figure, the presence of price caps makes the effective supply curve for energy both convex and concave in different regions. When operating with high loads, therefore, the derated supply curve may work just as well in estimating average prices.

13 Severin Borenstein, James B. Bushnell, and Frank A. Wolak, "Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market," *The American Economic Review*, Vol. 92, No. 5, December 2002, p. 1378.

14 Severin Borenstein, James B. Bushnell, and Frank A. Wolak, "Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market," *The American Economic Review*, Vol. 92, No. 5, December 2002, p. 1386. See also Paul L. Joskow and Edward Kahn, "A Quantitative Analysis of Pricing in California's Wholesale Electricity Market During Summer 2000," *The Energy Journal*, Vol. 23, No. 4, 2002, p. 12.

historical rates for other plants or other periods[15] "to reflect 'non-strategic' forced outage rates."[16]

Market Power, Outages and Withholding

There is a common perception that the 2000-2001 crisis period in the California electricity market saw unusually high plant outage rates. This perception is particularly important in analyzing the cause of the high prices because the high priced hours were typically hours of stage 1, 2 or 3 emergency, which means that the California Independent System Operator was short of capacity at any price. The high prices during these hours could therefore only be the result of the exercise of market power if capacity was being physically withheld from the market, i.e. not available at any price, which would be the case for capacity unavailable due to outages or deratings.

In addition, a conclusion that outages were unusually high in the restructured California market deserves examination since it contradicts experience elsewhere. In the Mid-Atlantic region of the PJM system, for example, the market monitor has found that the forced outage rate declined substantially after restructuring, falling from over 10% to under 5%. Moreover, the overall availability factor, taking account of both planned and maintenance outages rose after restructuring in PJM.[17] This trend in PJM reflects both improved performance of existing units and high performance by new units. Similarly, New York's independent market monitor found in an analysis of the initial year of New York Independent System Operator (NYISO) operation that more capacity was typically offered on units on high load days than had been available under earlier New York Power Pool operation.[18] In addition, the New York market monitor has generally found a negative relationship between the level of deratings and load levels, i.e. more capacity is available on high load, high priced days in the New York market.[19] One set of data bearing on this question in the California context is the outage data compiled by the California Energy Commission (CEC). Figure 2 depicts apparently higher than normal outage levels during the crisis period from the summer 2000 until summer 2001, apparently supporting the view that high prices arose in part from worse than normal generation availability.

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15 Severin Borenstein, James B. Bushnell, and Frank A. Wolak, "Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market," *The American Economic Review*, Vol. 92, No. 5, December 2002, used NERC data for 1993-1997, p. 1399.

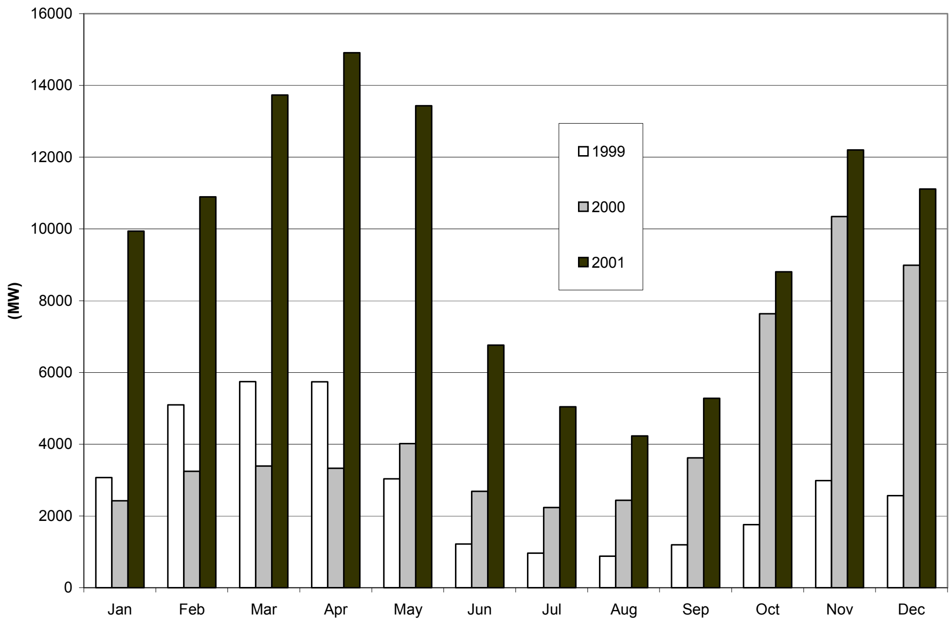
16 Paul L. Joskow and Edward Kahn, "A Quantitative Analysis of Pricing in California's Wholesale Electricity Market During Summer 2000," *The Energy Journal*, Vol. 23, No. 4, 2002, used NERC data for 1995-1999, p. 12.

17 PJM Market Monitoring Unit, "2002 State of the Market," March 5, 2003, p. 82-83.

18 David Patton, New York Market Advisor Annual Report on the New York Electric Markets for Calendar Year 2000, April 2001, pp. 58-60.

19 David Patton, New York Market Advisor Annual Report on the New York Electric Markets for Calendar Year 2000, April 2001, pp. 57-58; David Patton, 2001 Annual Report on the New York Electricity Markets, June 2002, p. v-vi, 21-22; David Patton, 2002 State of the Market Report New York ISO, June 2003, pp. 22-23.

Figure 2
CEC Calculation of Averaged Forced or Scheduled Megawatts Offline in California by Month



Source: CEC data is from www.energy.ca.gov/electricity/monthly_off_line.html.

However, these data have several limitations for the present discussion. For instance, the data are compiled from different sources from year to year and part of the year to year differences are likely attributable to differences in reporting standards.[20] In addition, the CEC numbers are most relevant for documenting the scarcity problems associated with an overall shortage of generating capacity. However, the CEC numbers are less relevant in identifying strategic physical withholding intended as a means of exercising market power because the totals include outages of nuclear plants and other sources (particularly Qualifying Facility (QF) capacity) owned by or under contract to utilities that were net buyers in the system and, therefore, would appear to have little incentive to withhold capacity in order to raise prices. Further, the CEC data do not distinguish between normal maintenance or forced outages and planned overhauls such as those for the installation of Selective Catalytic Reduction (SCR) technology for the control of nitrogen oxide (NOx) emissions that were required for continued operation of these units. Finally, these data portray the outage level, but not the outage rate. Since units that are off-line do not suffer forced outages, the level of capacity out is likely to be

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[20] The CEC website notes that these outage data are not comparable across years: "Filings of outages with the ISO have varied in consistency since June 1998, with incentives existing to both over- and under-report. The data, especially for periods prior to November 2000, may differ from outage values reported by other sources and in other documents, and should be considered indicative of general trends in unit outages, not as a precise measure of unavailable capacity." See www.energy.ca.gov/electricity/monthly_off_line.html.

higher during and following periods in which the units have been run more than during years in which the units have rarely operated.[21]

A different story appears in a comparison of a consistent set of data for thermal generators from a data base assembled by the U. S. Environmental Protection Agency (EPA) to monitor power plant emissions. Table 3 attached presents a consistent time series of the availability of thermal plants in California classified by their ownership status in 2000, grouped according to "Regulated Utility Units" and "Non-Utility Generator (NUG) Units" to reflect a distinction in the likely interest in exercising strategic behavior during the crisis. As net buyers with essentially fixed prices for their subsequent sales, the regulated utilities had an interest in lower prices. The NUG units are the focus of market power concerns with a possible incentive to act strategically to raise prices.

When we look at this data base which is compiled consistently over the period and excludes the capacity of the utility owned nuclear and coal plants as well as QF contracts, the opposite picture emerges. More units are on line for more hours during the crisis than in prior years (Table 3) and average hourly on-line capacity increased during the crisis period for these thermal plants as shown in Table 4 (attached). Moreover, the relative increase in availability appears to have been greater for the NUGs compared to the regulated utilities

While the EPA data provide a consistent comparison over the period and enable us to distinguish between the performance of thermal NUG units and other utility owned generation, Tables 3 and 4 do not enable us to identify generation that was unavailable due to long-term planned outages such as for SCR installation, nor do they show that the actual maintenance and outage rate during the crisis period was consistent with past experience. Although more capacity was on line during the crisis period than during prior years, much of the capacity that was off-line in prior years was off-line because it was not needed, not because it was unavailable. Finally, the EPA data is readily available only since late 1997, providing a relatively limited period for comparison.

Another set of outage data is available for the Mirant units, listed in Table 5. This is the outage data transferred to Mirant from PG&E in 1999, and the outage data compiled by Mirant over the subsequent period of operation through 2001. The Mirant thermal plants represent a substantial fraction of the NUG units in California. For example, in one analysis of NUG utilization, the Mirant plants accounted for 15.5% of the putative output "gap" in California. For the Northern California zones where the plants are located the figure is 97.9% of the

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[21] Thermal generating units cannot be dispatched down to zero output and then back up as needed. Instead, thermal units have minimum load levels required for stable operation. Most thermal plants also have relatively poor heat rate performance at minimum load (i.e., the number of Btus of energy consumed per MW generated is quite high) making it very expensive to keep the units on line during low load periods. Thermal units are therefore usually taken off line when they are not expected to be needed for a prolonged period.

putative output gap.[22] The plants covered in the Mirant data include ten conventional thermal plants, and three small combustion turbines not considered in this analysis.[23]

Table 5

Mirant Plants and Capacities

Mirant Thermal Units		
Plant	**Unit**	**Capacity (MW)**
Contra Costa	6	335
Contra Costa	7	337
Pittsburgh	1	150
Pittsburgh	2	150
Pittsburgh	3	150
Pittsburgh	4	145
Pittsburgh	5	312
Pittsburgh	6	317
Pittsburgh	7	682
Potrero	3	206

Table 6 summarizes the aggregate outage rate data for the Mirant plants under utility ownership (1994-1999) and the assumed outage rates used in one of the competitive market simulations.

Apparently the historical experience of the Mirant/PG&E plants under utility ownership and operation differed, sometimes substantially, from the performance pattern assumed in the counterfactual market simulation derived from national average data for plants of similar type and size.

The distinction between forced outage rates and normal maintenance can be important. For example, in the NERC data used in the simulations, the 8.51% effective forced outage rate corresponds to an effective total outage rate of 19.25%.[24] The maintained assumption in the counterfactual simulations is that capacity needed to meet load is unavailable only as a result of forced outages. The explicit assumption in these simulations is that all other maintenance or

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[22] Paul L. Joskow and Edward Kahn, "A Quantitative Analysis of Pricing in California's Wholesale Electricity Market During Summer 2000," *The Energy Journal*, Vol. 23, No. 4, 2002, used NERC data for 1995-1999, p. 23.

[23] The combustion turbines are a different type of unit designed for quick starts and operation for short periods of time. The Mirant combustion turbines were also subject to limitations on their hours of operation that were binding during the crisis.

[24] The NERC GADS data, 1995-1999, for fossil steam units "primary gas" of 300-399 MW. The national average Equivalent Forced Outage Rate (EFOR) is 8.51%. After accounting for maintenance outages and deratings, but excluding reserve shutdowns, the total Equivalent Availability Factor (EAF) is 80.75%, implying a total equivalent outage rate of 19.25%.

overhauls could be scheduled to occur only during low price hours when the plant is not needed.[25]

Table 6
Actual and Assumed Outage Rates (%) for PG&E/Mirant Units

	NERC/ Joskow-Kahn (A)	Annual Forced Outage 1994-1999 (B)	Annual Total Outage 1994-1999 (C)	Summer Forced Outage 1994-1999 (D)	Summer Total Outage 1994-1999 (E)
Contra Costa 6	8.51	23.64	31.41	6.88	16.57
Contra Costa 7	8.51	4.33	13.84	2.69	5.18
Average	8.51	13.99	22.63	4.79	10.88
Pittsburg 5	8.51	14.63	25.73	9.53	10.34
Pittsburg 6	8.51	2.00	12.66	0.58	20.56
Pittsburg 7	8.71	8.57	21.84	6.41	7.58
Average	8.58	8.40	20.08	5.51	12.83
Potrero 3	6.70	5.58	17.25	3.76	9.89
Pittsburg 1	10.30	50.45	56.61	48.69	52.12
Pittsburg 2	10.30	43.12	52.35	23.96	26.45
Pittsburg 3	10.30	66.70	74.18	42.26	45.44
Pittsburg 4	10.30	25.77	39.83	12.93	20.99
Average	10.30	46.51	55.74	31.96	36.25

(A) NERC GADS data, 1995 - 1999 Generating Unit Statistical Brochure, available at www.nerc.com/~filez/gar.html
(B) Forced outage hours January 1, 1994-December 31, 1998/ (forced outage + on-line hours)
(C) [Forced outage hours January 1, 1994-December 31, 1998/ (forced outage + on-line hours)] + [(maintenance hours/total hours)]
(D) Forced outage hours June 1 - September 30, 1994-1998/ (forced outage + on-line hours)
(E) [Forced outage hours June 1 - September 30, 1994-1998/ (forced outage + on-line hours)] + [(maintenance hours/total hours)]

Data Sources: Mirant Outage Data and The files CAL_SISO_4_Gen_Sch2_yyQ# from the CD "ISO Responses to Cal Parties First Set of DR, EL00-95 et al, Disk 2."

While it is correct that planned overhauls, as well as nuclear plant refuelings, are intended to take place during the shoulder months when the demand for capacity is reduced, these outages need to be spread out over time, increasing the likelihood that some outages will extend into a high demand period. Furthermore, while the timing of overhauls is planned to fall in non-peak periods, their ultimate duration sometimes cannot be controlled. For example, while Southern California Edison planned the refueling of its SONGS 3 unit to take place during the winter of 2001, the unit did not actually return to service until the end of May 2001, by which time its outage overlapped with PG&E's outage of Diablo Canyon 2, as well as several scheduled SCR installations.

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25 Paul L. Joskow and Edward Kahn, "A Quantitative Analysis of Pricing in California's Wholesale Electricity Market During Summer 2000," *The Energy Journal*, Vol. 23, No. 4, 2002, p. 12. Severin Borenstein, James B. Bushnell, and Frank A. Wolak, "Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market," *The American Economic Review*, Vol. 92, No. 5, December 2002, p. 1399.

Moreover, while planned overhauls and nuclear plant refuelings can be scheduled to fall during the shoulder months of the year, this is not the case for normal maintenance outages which are scheduled to repair short-term problems. These repairs do not require forced outages because they can be deferred to the end of the day or the end of the week, but they usually cannot be deferred several months until demand falls in the spring or fall. For example, as seen in Table 6, during the pre-crisis summer periods when demand was the highest, the outage rates included maintenance outages as well as periods recorded as forced outages. Apparently it would not take much deviation from this assumption of no maintenance outages to get the 5% outage error illustrated above.

These Mirant outage data permit us to examine the question of whether the level of outages was in fact higher during the crisis period than under prior utility ownership and operation. Table 7 (attached) compiles data on outages for each of the Mirant units over three periods. The period from May 22, 2000 through May 21, 2001 corresponds to the heart of the crisis period and Mirant operation. The second period is the one year period of Mirant operation prior to the crisis period from April 1, 1999 through March 31, 2000, and third the five years of PG&E ownership and operation from April 1, 1994 through March 31, 1999.[26]

Table 7 reports the total number of forced and maintenance outages and the number per year over the three periods. The table shows that the Mirant plants typically had more outages during the year of the crisis period than during an average year of PG&E ownership, so outages were higher by that measure. On the other hand, we also see that these units were on line far longer during the crisis period than was the case previously. Indeed, in the case of the Pittsburgh 1-4 units, they were on line almost as many hours during the one year of the crisis as during the last five years of PG&E ownership combined. If we then calculate the number of hours on line between forced or maintenance outages, we see that this figure is higher during the crisis period than before. Thus, Contra Costa 6 averaged 1096 hours between outages during the crisis period compared to 407 under PG&E ownership. Indeed, it can be seen that every one of the ten units performed better during the crisis by this metric. Finally, Table 7 also portrays the total output between outages and it is again seen that the total output between outage is higher under Mirant operation than under PG&E operation.

The differences between the average outage rates assumed for the counterfactual simulations and the actual data for the Mirant units may be specific to the units operated by Mirant. We might find that these assumed counterfactual outage rates overstate the historic outage rate of the other generation included in these simulations so that there is overall no systematic bias across the California plants. We do not have here similar data for other California plants to compare with the NERC national averages. In principle, therefore, it is possible that the errors average out across all California plants in the counterfactual simulations.

However, there is another possible bias that is even less likely to average out across all thermal generators. If high utilization is a contributor to higher failure rates, then ignoring the effect of high utilization during a period like the California crisis would be a systematic bias understating expected outage rates during the crisis period. The typical counterfactual

[26] These data have been compiled over annual periods to avoid distortions in the comparison due to seasonal patterns.

simulation makes no allowance for the impact on outage rates of increased stress on the thermal generating plants during periods of unusually high and sustained utilization. To the contrary, as mentioned, the typical approach has been to assume that maintenance can always be deferred to low price periods when the plant is not needed and that the forced outage rate is independent of utilization, thereby potentially understating the impact of outages on the cost of meeting load. The intent here is to examine the connection between utilization rates and failure rates and assess whether the counterfactual assumption of constant failure rate applies and whether outage rates were unusually high during the crisis period compared to the "non-strategic" predictions.

Hazard Rate Analysis

A full accounting for operating decisions, dispatch constraints and the economics of plant use is beyond the scope of this paper. Rather, the approach here is more an engineering analysis of plant operations within the framework of the counterfactual simulations. Assuming no strategic behavior, a plant operates and produces power. However, the duration of operation, level of utilization and other plant characteristics could affect the probability that the plant will fail or require maintenance that necessitates taking the unit off-line. The attempt here is to control for plant characteristics to produce a model "to reflect 'non-strategic' forced outage rates." Rather than assuming constant outage rates independent of utilization, we use the Mirant data to test this assumption. In addition, this allows a test of whether actual outage rates during the crisis were higher or lower than would have been predicted based on historical experience projected into a period of higher utilization.

The hazard rate model here treats a plant as either available or unavailable. Hence it does not account for "deratings" which are like partial outages. For example, in the NERC data base, the difference due to deratings of all types reduces the availability factor for an average 300 MW gas plant from 82.68% to an equivalent availability factor of 80.75%, for a difference of 1.93%.[27]

Failure Models

The model characterizes failures, either forced or maintenance outages, as random events drawn from a particular failure distribution. The density function describes the time to failure of the equipment, $f(t)$. The cumulative distribution for the probability that equipment fails at or before time t is:

$$F(t) = \int_0^t f(s)\, ds .$$

Given the cumulative failure distribution, the survival function is the probability that the equipment is still running at time t, as in:

$$S(t) = 1 - F(t) .$$

Finally, given the survival function the hazard rate as:

[27] NERC GADS data base, 1995-1999, Fossil-steam Units "Primary Gas" 3000-3999 MW..

$$r(t) = \frac{f(t)}{S(t)}.$$

The hazard rate is essentially the rate at which failures occur at time t given that the equipment has not yet failed. In general, hazard rates could vary over time. A constant hazard rate is a limiting case with an exponential failure distribution.

Perhaps the most commonly used empirical failure rate model is the so-called proportional hazard rate (PH) model developed by Cox.[28] A generic proportional hazard rate model assumes the existence of a base hazard rate, say $r_0(t)$, and a set of possibly time dependent covariate factors that would determine the hazard rate for individual plants, $Z_i(t)$.[29] The resulting model of the hazard rate for the individual plant would be:

$$r_i(t) = r_0(t) e^{Z_i(t)\beta},$$

or

$$\ln r_i(t) = \ln r_0(t) + Z_i(t)\beta.$$

In other words, the individual plant hazard rate $r_i(t)$ follows the base hazard rate but is scaled up our down by a function of the vector of covariates $Z_i(t)$ multiplied by the common coefficients in β.

A related approach to the proportional hazard rate model is found in the accelerated failure time (AFT) models. These approaches focus on characterizing the changes in expected failure time rather than the changes in the hazard rate. For example, in the loglinear case the basic model would be:

$$\ln(t_i) = \ln(t_0) + Z_i(t)\theta + \tau,$$
$$\tau \sim f(s).$$

The AFT parameterization is sometimes convenient for estimation, as in the case of a lognormal failure law. In the proportional hazard rate model, a negative value for β implies a lower hazard rate and therefore a longer expected time to failure. In the accelerated failure time models a positive θ implies a longer expected time to failure.

Maximum Likelihood Estimation

The estimation approach follows a sequential strategy.[30] The Cox semi-parametric approach allows a flexible base hazard rate but is not suited to answering the most important

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[28] D. R. Cox, "Regression Models and Life-Tables," *Journal of the Royal Statistical Society*, B, Vol. 26, 1972, pp. 186-220.

[29] John D. Kalbfleisch and Ross L. Prentice, *The Statistical Analysis of Failure Time Data*, Wiley, 2002, chapter. 4, pp. 95-147.

[30] All the estimation uses the STATA software system.

questions here. The Cox model provides a general support for subsequent parametric models which become the focus of the analysis.

The Cox semi-parametric proportional hazard rate approach makes no assumption about the form of the base hazard rate.[31] For simplicity, assume the data are ordered according to failure time with *n* total failures for $m \geq n$ possible units. The Cox model identifies failure of unit *i* at time *t* as having conditional probability:

$$\frac{r_0(t)e^{Z_i(t)\beta}}{\sum_{j=i}^{m} r_0(t)e^{Z_j(t)\beta}}.$$

The criterion for choosing the parameters β is to maximize the product of the conditional probabilities in the "partial likelihood" function,[32]

$$\prod_{i=1}^{n}\frac{r_0(t)e^{Z_i(t)\beta}}{\sum_{j=i}^{m} r_0(t)e^{Z_j(t)\beta}} = \prod_{i=1}^{n}\frac{e^{Z_i(t)\beta}}{\sum_{j=i}^{m} e^{Z_j(t)\beta}}.$$

In other words, there is no explicit estimation of the baseline hazard rate in $r_0(t)$.

The parametric approaches provides an explicit model of $r_0(t)$. Here, the conventional conditional likelihood for each observation is of the form

$$L_i[\beta,\Theta] = \frac{\left(S\left(t_i \mid Z_i(t)\beta,\Theta\right)\right)^{1-d_i}\left(f\left(t_i \mid Z_i(t)\beta,\Theta\right)\right)^{d_i}}{S\left(t_{0i} \mid Z_i(t)\beta,\Theta\right)},$$

where the vector Θ includes parameters of the failure distribution and $d_i = 1,0$ depending on whether the observation is a failure or not (censored) during the period $t_{0i} \leq t \leq t_i$. The covariates as defined are external variables and preserve the form of the likelihood function.[33] The estimation maximizes

$$L[\beta,\Theta] = \prod_{i=1}^{m} L_i[\beta,\Theta].$$

The explicit failure model of the parametric approach facilitates comparison of predicted outage rates.

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31 John D. Kalbfleisch and Ross L. Prentice, *The Statistical Analysis of Failure Time Data,* Wiley, New York, 2nd. Edition, 2002, pp. 101-103.

32 This is similar to the conditional logit model. William H. Greene, *Econometric Analysis*, 4th ed. Prentice Hall, 2000, pp. 862-864.

33 John D. Kalbfleisch and Ross L. Prentice, *The Statistical Analysis of Failure Time Data*, Wiley, New York, 2nd. Edition, 2002, pp. 196-197.

Forced and Maintenance Time Until Failure

In the present case we use data for the ten Mirant thermal plants. The outage data distinguish among four types of outages: major overhauls, forced outages, maintenance outages, and reserve shutdowns.

Major overhauls are unusual events coordinated by the CAISO and were required for the installation of SCR equipment. We do not consider these relevant for the study of possible strategic manipulation and these are not considered here.

Similarly, reserve shutdowns are periods in the historical data during which the units were off-line but were available to start if needed to meet load. Thus, reserve shutdowns are not like forced or maintenance outages. The plants were available but off-line because they were not needed. Hence, we treat reserve shutdowns as "time out" in the sense of stopping the clock rather than "time off line" in the sense of broken and unavailable. Thus, the analysis of time to unit failure is based on the time on-line rather than calendar time. Similarly, while generators typically use reserve shutdowns to undertake minor repairs to the unit, the extent of the repairs that can be undertaken is limited by the fact that the units remain available to be started if needed.

In principle, forced outages and maintenance outages could follow different failure distributions, but they differ in practice largely in the immediacy with which the unit must be taken off-line. For the purpose of this paper, we have treated forced and maintenance outages as alike in analyzing the effect of changed utilization and other control variables.

An application of the Cox PH model illustrates the effect of the crisis period. In particular, we first introduce a single variable "Crisis" that is zero for the pre-crisis period and one during the crisis. Then the resulting proportional hazard rate model would be

$$r_i\left(t\right) = r_0\left(t\right) e^{Crisis*\beta_{crisis}} .$$

The data for all the plants are pooled and the Cox procedure applied to determine the estimate of the coefficient of the crisis variable, β_{crisis}. During the pre-crisis period there would be no effect, and the base hazard rate model $r_0\left(t\right)$ would apply, but during the crisis the hazard rate would be multiplied by the factor $e^{\beta_{crisis}}$.

The result for the failure time estimation appears in Table 8 (attached) with $\beta_{crisis} = -0.150$. The sign indicates longer times between failures during the crisis period, but the coefficient is not statistically significant.

As a first step towards a parametric model, we apply an accelerated failure time parameterization with a generalized gamma distribution. The generalized gamma model is a complex accelerated failure time parametric model that is useful for deciding on which of the more restricted parametric models would be most applicable.[34] For failure time t_i, we have the generalized gamma with

[34] Mario A. Cleves, William W. Gould and Roberto G. Gutierrez, *An Introduction to Survival Analysis Using Stata*, Stata Press, 2002, pp. 225-226.

$$\tau_i = e^{-Z'\theta} t_i,$$
$$\tau_i \sim GGamma\left(\beta_0, \kappa, \sigma\right).$$

Given observed failure times, the maximum likelihood estimation provides the parameters $\left(\hat{\beta}_0, \hat{\kappa}, \hat{\sigma}, \hat{\theta}\right)$. If the so-called κ parameter is equal to unity then this specializes to the Weibull distribution familiar in engineering analysis. If the κ value is zero, then we have a lognormal failure law.

As shown in Table 8, for the simple model with a crisis variable only, the generalized gamma implementation has a coefficient of $\theta_{crisis} = 0.160$ implying longer failure times and lower failure rates during the crisis. Again the coefficient is not statistically significant.

The estimate of $\kappa = 1.128$ is not statistically different from one and suggests that a simpler model might be a Weibull failure law. Table 9 reports the corresponding estimate in the Weibull proportional hazards model as $\beta_{crisis} = -0.127$, which also implies lower failure rates during the crisis. The coefficient is not statistically significant, but this more tractable parametric model produces a result that is similar to that found in the Cox semi-parametric estimate. Based on these tests, we concluded that the Weibull proportional hazard rate model would be the most applicable parametric failure law.

The use of the parametric model with an explicit hazard rate plays a role in the test of behavior, strategic or otherwise, during the crisis period. The tests above used all of the data, which include the experience during the crisis period. However, the crisis period could be different for many reasons. It may be that there was strategic withholding to exercise market power, or it may be that there was an exceptional effort to keep plants running at capacity in order to profit from high prices due to scarcity. To accommodate both views, we estimate the parametric model only with the pre-crisis data.

The estimation proceeds in two stages. First, we restrict estimation to the period before the crisis, from 1994 to April of 2000. We obtain estimates of the pre-crisis coefficients $\hat{\beta}$ for the covariates defined in $Z_i\left(t\right)$. This model would replace the counterfactual assumption of a constant expected failure time as used in the typical single stack simulation model. Given these assumed "non-strategic" or "normal" estimates, we fix the coefficients and form a new model for the whole period with only a dummy variable for the crisis period. In effect, the coefficient for this crisis variable provides an estimate of the average impact on failures during the crisis as compared to what would have been expected based on the failure model estimated with pre-crisis data but applied to the actual utilization and other control variables during the crisis period.

The Weibull formulation of the parametric proportional hazard rate model is:

$$r_i\left(t\right) = pt^{p-1}e^{Z_i(t)\beta}.$$

The base hazard rate is constant if $p = 1$ and increasing or decreasing as p is greater or less than one, respectively. The Weibull model provides a framework for a better test of the effect of the California crisis.

Introducing variables to control for the intensity of use is a principal objective. We would expect a systematic difference in hazard rates for plants that are merely running at a relatively low capacity factor versus those plants that are running at nearly a full capacity for a sustained number of hours. For more intense usage it would be reasonable to expect a higher hazard rate.

The data include information on output and other characteristics of plants.

Control Variables (Z)

- Average capacity utilization since the last outage.
- Average capacity utilization between last overhaul and last outage.
- Number of forced outages since last overhaul
- Number of maintenance outages since last overhaul
- Elapsed calendar time since the last outage.
- On line time since the last overhaul.
- Plant/unit dummy variables
- Dummy variables for failures without a previous overhaul
- Dummy variable for "crisis" period.

These measures include fixed effects for individual plants to capture differences in plant characteristics like heat rates, average utilization since the last overhaul or outage, calendar time and time on line (*t*), and the "Crisis" variable. We also included counters for the number of outages as control variables to help pick up any difference in the opportunities to provide some maintenance and repair in addition to overhauls. The data include both "time varying" covariates the vary over the interval until plant failure or overhaul (e.g., calendar time since last overhaul), and fixed covariates that are constant over this interval (e.g., the number of maintenance outages since last overhaul).

We excluded outages that occurred within 24 hours of coming on-line after an outage on the grounds that this was a burn-in effect and just a continuation of the prior outage. Measurement of the time until the next failure begins when a plant comes back on line from an overhaul, maintenance or forced outage. This gives a substantial pool of failure and censored observations presumed to be conditionally independent that can be used in the maximum likelihood estimation.

In some cases at the start of the period there were failures or maintenance outages without data on the time since the last major overhaul. For these observations we set a dummy variable equal to one to indicate a pre-period major overhaul to account for the fact that we do not know exactly the overhaul time.

In the generalized gamma case in Table 8, we see that including the fixed plant effects increases the crisis coefficient from 0.160 to 0.350. Hence, when we control for plant characteristics we find that the estimated time to failure increases even further during the crisis. Now the crisis coefficient is statistically significant.

The κ parameter in the generalized gamma model with fixed plant effects is essentially the same as without. Hence, we focus on the Weibull model in Table 9 (attached) where the same analysis of the fixed effects model produces a crisis parameter of $\beta_{crisis} = \text{-}0.295$, again implying that outage rates were lower during the crisis period compared to the predictions of the pre-crisis model.

Finally, we see in Table 9 the application of the Weibull model to the data including control variables for utilization and previous outages. Again, the model coefficients for the control variables were estimated from the pre-crisis data and then applied to the full sample to estimate the separate effect of the crisis variable conditional on the expectations obtained from the pre-crisis model. The result is that the crisis coefficient becomes even more negative, now $\beta_{crisis} = -0.392$, implying longer periods between outages during the crisis period, and is statistically significant.

The parameters indicate that we have reasonable estimates of the control effects with higher utilization since the last outage and time since last outage. Further, as we expand the set of control variables, we find increasing evidence of a coefficient of the crisis variable that indicates that on average plant operations during the crisis differed from past behavior by keeping the plants running longer than would have been expected based on the "non-strategic" pre-crisis base line.

Outage Duration

The longer the on-line period between outages, other things being equal, the lower the total time the unit is unavailable. However, the other critical factor is the length of time that a plant remains unavailable after it has been forced out or taken out for normal maintenance. This duration of outage combines with the time on line to determine the percentage of time that plants are unavailable on average. The percentage of time a plant is unavailable due to outages is the ratio of the outage duration to the total of the online time and outage duration. The failure rate analysis addresses the online time component.

Absent a good understanding of the determinants of outage duration, we elected to treat outage duration in a way symmetric with the treatment of failure times. The only difference is that in the case a higher hazard rate implies a faster return to on-line status. Hence, the interpretation of all the coefficients reverses the sign of the effects from the failure rate model.

The principal modeling decision was to exclude major overhauls from the analysis of outage duration. It is our understanding that major overhauls must be approved by the CAISO and the timing was not within the control of the company. In addition, many of these outages were required for environmental compliance rather than conventional maintenance considerations. Hence, these outages would not reflect discretionary choices that might relate to market manipulation and their duration would be governed by the nature of the unit modifications being made. Other than major overhauls, we pooled the data for all types of outages. In contrast to the time until failure, where the covariates varied over the failure interval, the covariates for outage duration are fixed at the values at the beginning of the outage.

The results appear in Table 10 (attached), in essentially the same form as those for the failure analysis. Hence, when we use the simple model with only the crisis variable, the semi-parametric model indicates that the crisis had essentially no effect on availability.[35] The generalized gamma model yields a $\kappa = 0.120$ parameter and it is not statistically different from zero. Hence, the κ parameter supports the choice of the lognormal accelerated failure time model for the full parametric analysis.

The results in Table 11 (attached) for the full lognormal model suggest that the outage duration was lower during the crisis compared to what would have been expected based on a model estimated from the pre-crisis data. In particular, we have $\theta_{crisis} = -0.410$, and it is significant at the 5% level.

Implied Crisis Effect

A test for the change in percentage of time out between crisis and non-crisis periods is available from the parameters of the parametric failure time and outage duration models.

With a Weibull failure model with density function $f(t)$, for the base hazard rate $r_0(t)$ with shape parameter p and scale parameter β_0 we have:

$$r_0(t) = r_0(t) = pt^{p-1}\lambda^p, \textit{ where } \lambda^p = e^{\beta_0}.$$

Therefore, expected failure time is[36]

$$E(t) = \frac{1}{\lambda}\Gamma\left(1 + \frac{1}{p}\right).$$

For the lognormal model of outage duration time, with mean and variance of the logarithms of outage time (*o*) as μ, σ^2, we have the standard result for the lognormal distribution applied to the expected value of a duration of an outage:

$$E(o) = e^{\mu + \frac{\sigma^2}{2}}.$$

The usual definition of the outage rate evaluated at the expected values is:

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[35] Maintenance outages were also not entirely within the control of the generator during the crisis period as the Cal ISO often refused to approve requested maintenance outages. To the extent that these refusals ultimately resulted in outages that were longer than would have been the case had maintenance been undertaken when it was requested, increases in outage duration during the crisis could be attributable to Cal ISO command and control rather than strategic behavior.

[36] See the appendix for details. This applies for fixed covariates and is an approximation for the combined effect of the time dependent covariates.

$$\pi = \frac{E(o)}{E(t)+E(o)} = \frac{\bar{o}}{\bar{t}+\bar{o}}.$$

Then comparing crisis "*c*" and non-strategic prediction "*n*" we have

$$\frac{1}{\pi_c} - \frac{1}{\pi_n} = 1 + \frac{\bar{t}_c}{\bar{o}_c} - 1 - \frac{\bar{t}_n}{\bar{o}_n} = \frac{\bar{t}_c}{\bar{o}_c} - \frac{\bar{t}_n}{\bar{o}_n}.$$

For the Weibull failure model we have for the crisis coefficient:

$$\eta^p = e^{\beta_{crisis}},$$

$$with$$

$$r_c(t) = r_n(t)e^{\beta_{crisis}} = pt^{p-1}(\eta\lambda)^p.$$

$$\frac{\bar{t}_c}{\bar{t}_n} = \frac{\frac{1}{\eta\lambda}\Gamma\left(1+\frac{1}{p}\right)}{\frac{1}{\lambda}\Gamma\left(1+\frac{1}{p}\right)} = \frac{1}{\eta}.$$

For the lognormal duration model we have:

$$\frac{\bar{o}_c}{\bar{o}_n} = \frac{e^{\mu + Crisis*\theta_{crisis} + \frac{\sigma^2}{2}}}{e^{\mu+\frac{\sigma^2}{2}}} = e^{\theta_{crisis}}.$$

Hence,

$$\frac{1}{\pi_c} - \frac{1}{\pi_n} = \frac{\bar{t}_c}{\bar{o}_c} - \frac{\bar{t}_n}{\bar{o}_n} = \frac{\frac{1}{\eta}\bar{t}_n}{e^{\theta_{crisis}}\bar{o}_n} - \frac{\bar{t}_n}{\bar{o}_n} = \left[\frac{1}{\eta e^{\theta_{crisis}}} - 1\right]\frac{\bar{t}_n}{\bar{o}_n}.$$

Therefore, we find for

$$\pi_c \le \pi_n,$$

we must have

$$\phi = \ln\left(\eta e^{\theta_{crisis}}\right) = \frac{\beta_{crisis}}{p} + \theta_{crisis} \le 0.$$

The failure and outage duration regression models provide estimates of these parameters and their associated standard errors. If ϕ is negative, then the percentage of time unavailable is lower than would be expected during the crisis after controlling for utilization and other effects. If ϕ is positive, then the percentage time off-line is higher than would be expected during the crisis.

From the tables we can see that the maximum likelihood estimate of the parameter is:

$$\phi = \frac{\beta_{crisis}}{p} + \theta_{crisis} = \frac{-0.392}{0.567} - 0.410 = -1.10.$$

Hence, the combined effect of longer running times and shorter outage durations during the crisis, after controlling for other effects, is consistent with the conclusion that the actual percentage of time unavailable was less during the crisis period than expected from the pre-crisis model.

The standard errors for the parameters provide a combined standard error ϕ. For simplicity, we apply a conservative case for the shape parameter p by setting it to its end point for a 95% confidence interval ($0.518 \le p \le 0.621$) in calculating an estimate of the standard error. If the two estimates for failure rates and outage durations are independent, then

$$\sigma_\phi \approx \sqrt{\left(\frac{s_{\beta_{crisis}}}{p}\right)^2 + s^2_{\theta_{crisis}}} = \sqrt{\left(\frac{0.118}{0.518}\right)^2 + (0.182)^2} = 0.291.$$

This implies an approximate z-statistic of

$$z = \frac{\phi - 0}{\sigma_\phi} = \frac{-1.10}{0.291} = -3.78.$$

Given these assumptions, therefore, the estimates from the exploratory statistical model are statistically significant and consistent with the interpretation that plants had lower outage rates during the crisis than would be predicted by the non-strategic baseline after controlling for changes in utilization and the other factors.

Baseline Outage Rates

Establishing the sign of the difference between the counterfactual and crisis outage rates and determining that this difference was statistically significant does not quantity the size of the effect. In addition, it does not identify the difference between the historical outage rate and the prediction for the crisis period baseline with higher utilization and with no strategic effects

We have an estimated historical outage rate model π_h for these plants. Conceptually, this historic outage rate corresponds to the rate one might use in a counterfactual simulation.[37] However, we would like to understand the sign and magnitude of any bias introduced by assuming the historical outage rate should be a good predictor of the normal outage rate under the stressed conditions of the crisis period. Hence, we consider the difference in expected outage rates, such as

$$\Delta_h = \pi_n - \pi_h.$$

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[37] The model in π_h reflects the historic outage performance of the specific units whose performance is being examined, while the principal counterfactual simulations of the California market have used national averages that are not necessarily applicable to the California units, which can have different emissions and cooling systems.

where π_n is the estimated outage rate with higher utilization and with no strategic effects. Determining the level of the outage rate requires calculation of the expected failure time and the expected outage duration under different conditions.

Although not difficult in principle, calculation of the expected failure times requires assumptions about the trajectory of the time varying covariates. For example, the utilization rate varies over the failure interval. Although we can observe the variation of the utilization rate over the sample period up until the observed time of failure, calculation of the expected time to failure requires a characterization of the utilization rate over the infinite horizon after the failure occurs. If there is a trend in the variables, this could make a difference. Similar problems do not arise with the duration of an outage, where the covariates are fixed at the beginning of the outage.

To accommodate various assumptions about the trajectory, we calculated different capacity weighted point estimates of Δ and its components. In the first instance, we assumed that all covariates were fixed at the sample averages for each unit during the period but set the crisis dummy to zero. For covariates that are generally increasing and have a positive coefficient, this simplification tends to increase the hazard rate in the early part of the interval and decrease the implied hazard rate in the later part of the interval. The net effect could increase or decrease the expected failure time. Hence,

$$\Delta_h^{Mean} = \pi\left(\bar{Z}_{Crisis}, Crisis = 0\right) - \pi\left(\bar{Z}_{Pre-crisis}, Crisis = 0\right).$$

To illustrate the magnitude of the effect of the crisis, one comparison is of the projection at the covariate means and the same projection with the crisis dummy variable at unity:

$$\Delta_c^{Mean} = \pi\left(\bar{Z}_{Crisis}, Crisis = 1\right) - \pi\left(\bar{Z}_{Crisis}, Crisis = 0\right).$$

The other versions all involve numerical integration of the failure time model for each failure interval. The assumption here is that the post failure trajectory for utilization is the last observation, and that the other time dependent covariates increase with the time on-line assuming no reserve shutdowns or planned outages.

To illustrate the incremental effect of utilization alone, we examined only the change in utilization between the crisis and pre-crisis period. All the covariates other than utilization since the last outage follow the pre-crisis values ($\tilde{Z}_{Pre-crisis}$), while the utilization trajectory is scaled by the ratio of the plant specific average utilization in the sample for the crisis and pre-crisis periods. The outage rate for each unit is calculated based on the average time to failure and outage duration across the sample of outages. The capacity weighted average is then calculated across all units. This is an estimate of the incremental effect of utilization alone, as in

$$\Delta_h^{Iutil} = \bar{\pi}\left(\frac{\bar{U}_{crisis}}{\bar{U}_{Pre-crisis}} U_{Pre-crisis}, \tilde{Z}_{Pre-crisis}, Crisis = 0\right) - \bar{\pi}\left(U_{Pre-crisis}, \tilde{Z}_{Pre-crisis}, Crisis = 0\right).$$

The final variant calculates the average difference across the observation in both periods. This includes all the variation in the covariate factors reflecting behavior during the crisis period.

$$\Delta_h^{Dynamic} = \bar{\pi}\left(Z_{Crisis}, Crisis = 0\right) - \bar{\pi}\left(Z_{Pre-crisis}, Crisis = 0\right).$$

Table 12 summarizes the results, aggregating them across the units on a capacity weighted basis, as well as bootstrap estimates of the mean difference and the standard error of the difference.[38]

Table 12

Mirant Plants					
Estimated Capacity Weighted Outage Rates					
	Point Estimate	**Point Estimate**	**Difference**	**Bootstrap Mean**	**Bootstrap Standard Error**
	$\pi\left(\bar{Z}_{Pre-crisis}, C=0\right)$	$\pi\left(\bar{Z}_{Crisis}, C=0\right)$	Δ	$\bar{\Delta}$	$s.e\left(\Delta\right)$
At Means: No Crisis Effect	18.75%	26.65%	7.90%	7.92%	3.50%
	$\pi\left(\bar{Z}_{Crisis}, C=0\right)$	$\pi\left(\bar{Z}_{Crisis}, C=1\right)$			
At Means: Crisis Effect	26.65%	12.65%	-14.00%	-13.31%	5.22%
	$\bar{\pi}\left(U_{Pre-crisis}, \bullet, C=0\right)$	$\bar{\pi}\left(\frac{\bar{U}_{crisis}}{\bar{U}_{Pre-crisis}} U_{Pre-crisis}, \bullet, C=0\right)$			
Dynamic: Incremental Utilization	17.36%	21.07%	3.71%	3.59%	0.84%
	$\bar{\pi}\left(Z_{Pre-crisis}, C=0\right)$	$\bar{\pi}\left(Z_{Crisis}, C=0\right)$			
Dynamic: Total No Crisis Effect	17.36%	19.80%	2.44%	4.88%	2.95%

The focus here is on the outage rates for maintenance and forced outages. The implication is that the capacity weighted point estimate of the counterfactual outage rate during the crisis would be higher than the historical average. Further, the estimated effect of behavior during the crisis period is to reduce the expected outage rates below both the counterfactual prediction and the historical performance. Although the exact magnitude of the difference between an outage rate based on historical performance and that accounting for higher utilization during the crisis period depends on the assumption about the behavior of the covariates such as utilization and maintenance activity, the estimated differences could be important. The bias resulting from use of historical outage rates would be sufficient to materially increase any estimate of the difference between the counterfactual and observed market prices.

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[38] The bootstrap is based on 500 replications, with stratified samples for crisis and plant dummies. The outage rate estimates are for observations with data on prior overhauls. In a few bootstrap replications a plant dummy coefficient has a large value and a much larger standard error In these cases the outage rate estimate drops the plant dummy variable.

Conclusion

Thermal generators were operating under stressed conditions during the California electricity crisis. The generally higher utilization rates during the crisis period than during prior years would contribute to higher outage rates during the crisis period, other things being equal. However, the estimation of the hazard rate model shows that other things were not equal and that the expected outage rates in the crisis period were significantly and materially lower than the predictions of the non-strategic model based on pre-crisis outage performance. The differential suggests that counterfactual simulations based on historical outage rates would tend to understate the competitive price during the kind of sustained crisis conditions that prevailed in California. Further, the empirical analysis indicates that the actual behavior of this generator operated to increase generation availability and thus lower prices relative to what the competitive price would have been under the non-strategic predictions for outage rates based on pre-crisis performance. This outcome would be consistent with the high prices prevailing during the shortage conditions motivating the generator to make extra-ordinary efforts to keep the units on line.

Table 3
Monthly Hours Generating – Selected California Utility and NUG Units, 1997-2001

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total Jan-Dec	Total Jan-May	Total Jun-Dec
						Regulated Utility Units									
1997	-	-	-	-	-	-	-	-	-	7,746	4,527	4,218	NM	NM	NM
1998	4,443	4,232	4,598	4,644	5,600	6,051	12,083	15,498	12,750	8,681	7,126	6,691	92,397	23,517	68,880
1999	5,427	5,425	7,098	6,289	7,930	11,277	13,362	13,397	10,302	14,804	8,836	8,564	112,711	32,169	80,542
2000	10,725	8,719	8,857	8,014	12,690	14,885	17,311	18,727	14,709	12,184	9,968	10,803	147,592	49,005	98,587
2001	11,480	9,899	10,719	8,940	12,200	12,729	14,528	15,421	13,304	11,888	8,433	8,246	137,787	53,238	84,549
						Non-Utility (NUG) Units									
1997	-	-	-	-	-	-	-	-	-	16,806	12,322	13,883	NM	NM	NM
1998	15,451	12,266	13,746	12,132	11,175	13,590	23,236	28,805	23,636	19,149	15,176	15,766	204,128	64,770	139,358
1999	17,110	14,852	14,363	16,853	15,043	17,956	25,110	25,458	21,675	29,667	18,043	17,618	233,748	78,221	155,527
2000	19,529	17,772	15,619	15,015	22,125	29,484	32,093	36,083	31,757	29,310	22,750	26,375	297,912	90,060	207,852
2001	30,300	25,658	28,731	26,977	25,890	27,009	33,005	34,396	27,762	23,013	20,566	22,324	325,631	137,556	188,075
						Total Regulated Utility and Non-Utility (NUG) Units									
1997	-	-	-	-	-	-	-	-	-	24,552	16,849	18,101	NM	NM	NM
1998	19,894	16,498	18,344	16,776	16,775	19,641	35,319	44,303	36,386	27,830	22,302	22,457	296,525	88,287	208,238
1999	22,537	20,277	21,461	23,142	22,973	29,233	38,472	38,855	31,977	44,471	26,879	26,182	346,459	110,390	236,069
2000	30,254	26,491	24,476	23,029	34,815	44,369	49,404	54,810	46,466	41,494	32,718	37,178	445,504	139,065	306,439
2001	41,780	35,557	39,450	35,917	38,090	39,738	47,533	49,817	41,066	34,901	28,999	30,570	463,418	190,794	272,624

Source: EPA CEMS Data

Note 1: This table reports the number of hours in a given month that California Non Utility Generators and Regulated Utility Units report generation to CEMS. Many units do not report CEMS data, and therefore must be excluded from this table. Units excluded due to lack of data: Alnor, Brawley, Coachella, Downieville, Ellwood, Glenarm, Kearny, Kern, Kings Beach, Long Beach, McClellan, McClure Mountainview, North Island, Oakland, Pebbly Beach, Portola, Redding Power, Rockwood, Walnut. Units included in this table are: Alamitos, Broadway, Contra Costa, Coolwater, El Centro, El Segundo, Encina, Etiwanda, Grayson, Harbor, Haynes, Humbolt Bay, Hunters Point (Partial - see note 2), Huntington Beach, Magnolia, Mandalay, Morro Bay, Moss Landing, Olive, Ormond Beach, Pittsburg, Potrero, Redondo Beach, Riverside, Scattergood, South Bay, Valley and Woodland.

Note 2: In this time period Hunters Point 3-6 reported hourly steam load output, but no hourly gross generation. These units are excluded from this table because it is unclear whether they were producing electricity.

Table 4
Average Hourly Capacity On-Line – Selected California Utility and NUG Units, 1997-2001

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average Jan-Dec	Average Jan-May	Average Jun-Dec
	Regulated Utility Units														
1997	-	-	-	-	-	-	-	-	-	1,432	656	458	NM	NM	NM
1998	556	568	545	575	827	915	1,960	2,738	2,182	1,357	1,009	810	1,175	615	1,570
1999	780	1,009	1,300	1,166	1,481	2,256	2,773	2,687	1,976	2,605	1,530	1,351	1,749	1,150	2,172
2000	1,665	1,518	1,599	1,043	1,839	2,444	2,981	3,248	2,451	1,817	1,441	1,687	1,982	1,536	2,298
2001	1,800	1,870	1,639	1,447	1,859	1,894	2,116	2,520	2,178	1,755	1,173	1,135	1,783	1,722	1,826
	Non-Utility (NUG) Units														
1997	-	-	-	-	-	-	-	-	-	7,647	5,713	6,293	NM	NM	NM
1998	6,634	5,743	5,812	5,046	4,326	5,928	9,625	11,679	9,962	7,136	6,556	6,536	7,095	5,511	8,213
1999	6,981	6,582	5,710	6,380	5,688	7,254	8,566	8,709	7,774	11,591	7,437	6,828	7,468	6,261	8,320
2000	6,604	6,732	5,938	5,846	9,013	12,401	12,717	13,627	12,376	10,708	9,292	9,999	9,616	6,834	11,592
2001	10,742	10,729	10,537	10,197	10,116	11,535	12,518	13,402	11,730	9,948	8,114	9,240	10,738	10,461	10,933
	Total Regulated Utility and Non-Utility (NUG) Units														
1997	-	-	-	-	-	-	-	-	-	9,079	6,369	6,751	NM	NM	NM
1998	7,190	6,311	6,356	5,622	5,153	6,843	11,585	14,417	12,144	8,493	7,565	7,346	8,270	6,126	9,783
1999	7,761	7,591	7,010	7,545	7,169	9,509	11,339	11,396	9,750	14,196	8,967	8,179	9,217	7,411	10,492
2000	8,269	8,251	7,536	6,889	10,851	14,845	15,698	16,875	14,827	12,525	10,733	11,686	11,598	8,370	13,890
2001	12,542	12,599	12,177	11,644	11,975	13,430	14,634	15,922	13,908	11,703	9,288	10,374	12,521	12,183	12,759

Source: EPA CEMS Data. Capacity values come from EIA form 806, EIA Inventory of Nonutility Electric Power Plants in the United States 1999, and EIA Inventory of Utility Electric Power Plants in the United States 1999.

Note 1: This table reports the average hourly capacity, by month, of the generators that were online in the particular hour. Many units do not report CEMS data, and therefore must be excluded from this table. Units excluded due to lack of data: Alnor, Brawley, Coachella, Downieville, Ellwood, Glenarm, Kearny, Kern, Kings Beach, Long Beach, McClellan, McClure Mountainview, North Island, Oakland, Pebbly Beach, Portola, Redding Power, Rockwood, Walnut. Units included in this table are: Alamitos, Broadway, Contra Costa, Coolwater, El Centro, El Segundo, Encina, Etiwanda, Grayson, Harbor, Haynes, Humbolt Bay, Hunters Point (Partial - see note 2), Huntington Beach, Magnolia, Mandalay, Morro Bay, Moss Landing, Olive, Ormond Beach, Pittsburg, Potrero, Redondo Beach, Riverside, Scattergood, South Bay, Valley and Woodland.

Note 2: In this time period Hunters Point 3-6 reported hourly steam load output, but no hourly gross generation. These units are excluded from this table because it is unclear whether they were producing electricity.

Table 7
Mirant Plants 1994-2001

Contra Costa 6

Time Period	Forced Outages [1]	Maintenance Outages [1,2]	Total Non-RS Outages per Year	# of Hours Online	Hours Online per Forced Outage	Hours Online per Non-RS Outage	Total MW Generated	Total MW per Non-RS Outage
5/22/00 through 5/21/01	4	2	6	6,578	1,644	1,096	1,509,485	251,581
4/1/99 through 3/31/00	2	2	4	6,738	3,369	1,684	1,201,089	300,272
4/1/94 through 3/31/99	28	15	9	23,525	840	406	4,589,256	106,727

Contra Costa 7

Time Period	Forced Outages [1]	Maintenance Outages [1,2]	Total Non-RS Outages per Year	# of Hours Online	Hours Online per Forced Outage	Hours Online per Non-RS Outage	Total MW Generated	Total MW per Non-RS Outage
5/22/00 through 5/21/01	4	3	7	7,620	1,905	1,089	1,911,938	273,134
4/1/99 through 3/31/00	2	2	4	6,970	3,485	1,743	1,215,373	303,843
4/1/94 through 3/31/99	42	25	13	24,638	587	268	4,740,845	70,759

Pittsburg 1

Time Period	Forced Outages [1]	Maintenance Outages [1,2]	Total Non-RS Outages per Year	# of Hours Online	Hours Online per Forced Outage	Hours Online per Non-RS Outage	Total MW Generated	Total MW per Non-RS Outage
5/22/00 through 5/21/01	11	1	12	5,267	479	439	491,534	40,961
4/1/99 through 3/31/00	5	2	7	2,748	550	393	155,871	22,267
4/1/94 through 3/31/99	19	14	7	8,226	433	175	697,898	21,148

Pittsburg 2

Time Period	Forced Outages [1]	Maintenance Outages [1,2]	Total Non-RS Outages per Year	# of Hours Online	Hours Online per Forced Outage	Hours Online per Non-RS Outage	Total MW Generated	Total MW per Non-RS Outage
5/22/00 through 5/21/01	13	1	14	5,588	430	399	533,396	38,100
4/1/99 through 3/31/00	3	3	6	3,938	1,313	656	223,398	37,233
4/1/94 through 3/31/99	19	16	7	9,596	505	188	837,095	23,917

Pittsburg 3

Time Period	Forced Outages [1]	Maintenance Outages [1,2]	Total Non-RS Outages per Year	# of Hours Online	Hours Online per Forced Outage	Hours Online per Non-RS Outage	Total MW Generated	Total MW per Non-RS Outage
5/22/00 through 5/21/01	13	-	13	4,293	330	330	424,372	32,644
4/1/99 through 3/31/00	2	2	4	807	404	202	48,569	12,142
4/1/94 through 3/31/99	30	10	8	7,487	250	150	683,545	17,089

Table 7 continued on following page.

Table 7 (continued)

Pittsburg 4								
Time Period	Forced Outages [1]	Maintenance Outages [1,2]	Total Non-RS Outages per Year	# of Hours Online	Hours Online per Forced Outage	Hours Online per Non-RS Outage	Total MW Generated	Total MW per Non-RS Outage
5/22/00 through 5/21/01	4	5	9	5,965	1,491	663	621,024	69,003
4/1/99 through 3/31/00	3	1	4	1,343	448	336	88,628	22,157
4/1/94 through 3/31/99	26	15	8	7,123	274	127	656,483	16,012

Pittsburg 5								
Time Period	Forced Outages [1]	Maintenance Outages [1,2]	Total Non-RS Outages per Year	# of Hours Online	Hours Online per Forced Outage	Hours Online per Non-RS Outage	Total MW Generated	Total MW per Non-RS Outage
5/22/00 through 5/21/01	3	5	8	6,920	2,307	865	1,572,054	196,507
4/1/99 through 3/31/00	2	2	4	4,896	2,448	1,224	652,864	163,216
4/1/94 through 3/31/99	35	15	10	24,144	690	371	3,825,312	76,506

Pittsburg 6								
Time Period	Forced Outages [1]	Maintenance Outages [1,2]	Total Non-RS Outages per Year	# of Hours Online	Hours Online per Forced Outage	Hours Online per Non-RS Outage	Total MW Generated	Total MW per Non-RS Outage
5/22/00 through 5/21/01	3	4	7	7,506	2,502	1,072	1,896,931	270,990
4/1/99 through 3/31/00	3	3	6	4,836	1,612	806	631,831	105,305
4/1/94 through 3/31/99	21	26	9	29,841	1,421	409	4,702,918	100,062

Pittsburg 7								
Time Period	Forced Outages [1]	Maintenance Outages [1,2]	Total Non-RS Outages per Year	# of Hours Online	Hours Online per Forced Outage	Hours Online per Non-RS Outage	Total MW Generated	Total MW per Non-RS Outage
5/22/00 through 5/21/01	5	7	12	7,829	1,566	652	4,544,488	378,707
4/1/99 through 3/31/00	3	1	4	3,957	1,319	989	1,242,792	310,698
4/1/94 through 3/31/99	21	19	8	24,479	1,166	415	11,453,226	286,331

Potrero 3								
Time Period	Forced Outages [1]	Maintenance Outages [1,2]	Total Non-RS Outages per Year	# of Hours Online	Hours Online per Forced Outage	Hours Online per Non-RS Outage	Total MW Generated	Total MW per Non-RS Outage
5/22/00 through 5/21/01	3	6	9	6,681	2,227	742	994,864	110,540
4/1/99 through 3/31/00	7	5	12	6,180	883	515	783,496	65,291
4/1/94 through 3/31/99	16	19	7	32,591	2,037	604	4,174,431	119,269

Notes: (1) The counts of outages by type include any outage that began within the relevant time period. Any outage that starts less than sixty minutes after the previous outage ends has been merged with the previous outage. (2) Maintenance outages include overhauls.

Data Sources: Mirant Outage Data and The files CAL_SISO_4_Gen_Sch2_yyQ# containing data from the CD "ISO Responses to Cal Parties First Set of DR, EL00-95 et al, Disk 2."

Table 8
Plant Outage Model Results
Gamma Distribution and Cox Method

Regression	(A)	(B)	(C)
Methodology	Cox	Gamma	Gamma
Observations	13893	13893	13893
Number of Outages	466	466	466
Average Utilization Since Last Outage			
Average Utilization- Last Overhaul to Last Outage			
On-line Hours Since Last Overhaul			
Calender Time Since Last Outage			
Number of Previous Outages [1]			
Number of Previous Maintenance Outages [1]			
Contra Costa 6- Previous to First Overhaul			
Contra Costa 7- Previous to First Overhaul			
Pittsburg 3- Previous to First Overhaul			
Pittsburg 5- Previous to First Overhaul			
Pittsburg 6- Previous to First Overhaul			
Pittsburg 7- Previous to First Overhaul			
Petrero 3- Previous to First Overhaul			
Contra Costa 6			-0.469
			(1.64)
Contra Costa 7			-0.844
			(3.22)**
Pittsburg 1			-1.354
			(4.68)**
Pittsburg 2			-1.209
			(4.26)**
Pittsburg 3			-1.569
			(5.29)**
Pittsburg 4			-1.680
			(5.82)**
Pittsburg 5			-0.634
			(2.31)*
Pittsburg 6			-0.430
			(1.55)
Pittsburg 7			-0.298
			(1.00)
Constant		10.533	11.356
		(102.72)**	(52.35)**
kappa	--	1.128	1.241
		(9.18)**	(8.80)**
sigma	--	1.253	1.133
95% conf. Interval Upper		1.38	1.26
Lower		1.14	1.02
Crisis	-0.150	0.160	0.350
	(1.26)	(1.07)	(2.69)**

Absolute value of z statistics in parentheses
* significant at 5%; ** significant at 1%
(1) since last overhaul
Note: All variables have been scaled so that a value of 1 represents the mean value of the variable across the entire sample. Failure time is measured in minutes.

Data Sources: Mirant Outage Data and the files CAL_SISO_4_Gen_Sch2_yyQ# containing data from the CD "ISO Responses to Cal Parties First Set of DR, EL00-95 et al, Disk 2."

Table 9
Plant Outage Model Results
Weibull Distribution

Regression	(A)	(B)	(C)
Observations	13893	13893	13893
Number of Outages	466	466	466
Average Utilization Since Last Outage			0.819
			(5.64)**
Average Utilization- Last Overhaul to Last Outage			0.042
			(0.58)
On-line Hours Since Last Overhaul			-0.088
			(0.53)
Calender Time Since Last Outage			0.373
			(5.50)**
Number of Previous Outages [1]			-0.118
			(0.76)
Number of Previous Maintenance Outages [1]			0.124
			(0.56)
Contra Costa 6- Previous to First Overhaul			-1.292
			(1.26)
Contra Costa 7- Previous to First Overhaul			-1.001
			(0.99)
Pittsburg 3- Previous to First Overhaul			-0.437
			(0.59)
Pittsburg 5- Previous to First Overhaul			0.733
			(1.87)
Pittsburg 6- Previous to First Overhaul			-10.78
			(0.01)
Pittsburg 7- Previous to First Overhaul			-0.342
			(0.67)
Petrero 3- Previous to First Overhaul			0.108
			(0.28)
Contra Costa 6		0.464	0.566
		(1.910)	(1.71)
Contra Costa 7		0.762	0.871
		(3.39)**	(2.85)**
Pittsburg 1		1.148	1.126
		(4.51)**	(2.97)**
Pittsburg 2		1.020	1.065
		(4.09)**	(2.80)**
Pittsburg 3		1.357	1.828
		(5.23)**	(2.34)*
Pittsburg 4		1.460	1.406
		(5.81)**	(3.97)**
Pittsburg 5		0.541	0.303
		(2.26)*	(0.71)
Pittsburg 6		0.374	0.583
		(1.55)	(1.81)
Pittsburg 7		0.271	0.299
		(1.05)	(0.87)
Constant	-8.076	-9.326	-7.596
	(25.97)**	(21.94)**	(14.50)**
Shape parameter -- ln(p)	-0.258	-0.189	-0.577
	(7.06)**	(4.63)**	(6.76)**
Crisis	-0.127	-0.295	-0.392
	(1.07)	(2.50)*	(3.32)**

Absolute value of z statistics in parentheses
* significant at 5%; ** significant at 1%
(1) since last overhaul

Note: All variables have been scaled so that a value of 1 represents the mean value of the variable across the entire sample. Failures times are measured in minutes.

Data Sources: Mirant Outage Data and the files CAL_SISO_4_Gen_Sch2_yyQ# containing data from the CD "ISO Responses to Cal Parties First Set of DR, EL00-95 et al, Disk 2."

Table 10
Length of Outage Model Results
Gamma Distribution and Cox Method

Regression:	(A)	(B)	(C)	(D)
Distribution	Cox	Gamma	Gamma	Gamma
Observations	519	519	519	519
Number of Outages	519	519	519	519
Average Utilization Since Last Outage				-0.013
				(0.08)
Average Utilization- Last Overhaul to Last Outage				-0.137
				(1.79)
On-line Hours Since Last Overhaul				-0.161
				(0.56)
Calender Time Since Last Outage				0.155
				(1.61)
Number of Previous Outages [1]				0.197
				(0.76)
Number of Previous Maintenance Outages [1]				0.173
				(0.51)
Contra Costa 6- Previous to First Overhaul				-1.30
				(0.77)
Contra Costa 7- Previous to First Overhaul				-1.20
				(0.72)
Pittsburg 3- Previous to First Overhaul				-0.69
				(0.57)
Pittsburg 5- Previous to First Overhaul				-0.169
				(0.28)
Pittsburg 7- Previous to First Overhaul				0.593
				(0.72)
Petrero 3- Previous to First Overhaul				0.723
				(1.10)
Contra Costa 6			-0.855	-0.596
			(2.13)*	(1.09)
Contra Costa 7			-1.300	-0.998
			(3.53)**	(1.97)*
Pittsburg 1			-0.412	-0.338
			(1.03)	(0.56)
Pittsburg 2			-0.266	-0.238
			(0.65)	(0.38)
Pittsburg 3			0.130	0.900
			(0.31)	(0.71)
Pittsburg 4			-0.409	-0.429
			(1.02)	(0.72)
Pittsburg 5			-0.644	-0.276
			(1.66)	(0.41)
Pittsburg 6			-0.908	-0.607
			(2.28)*	(1.13)
Pittsburg 7			-0.589	-0.348
			(1.44)	(0.64)
Constant		7.953	8.600	8.225
		(63.98)**	(28.10)**	(16.45)**
kappa	--	0.134	0.207	0.193
		(1.26)	(1.78)	(1.56)
sigma	--	1.749	1.678	1.653
95% conf. Interval Upper		1.86	1.80	1.77
Lower		1.64	1.57	1.54
Crisis	0.043	-0.094	-0.188	-0.308
	(0.37)	(0.46)	(0.98)	(1.60)

Absolute value of z statistics in parentheses
* significant at 5%; ** significant at 1%
(1) since last overhaul
Note: All variables have been scaled so that a value of 1 represents the mean value of the variable across the entire sample. Failures times are measured in minutes.
Data Sources: Mirant Outage Data and the files CAL_SISO_4_Gen_Sch2_yyQ# containing data from the CD "ISO Responses to Cal Parties First Set of DR, EL00-95 et al, Disk 2."

Table 11
Length of Outage Model Results
Lognormal Distribution

Regression:	(A)	(B)	(C)
Observations	519	519	519
Number of Outages	519	519	519
Average Utilization Since Last Outage			-0.003
			(0.02)
Average Utilization- Last Overhaul to Last Outage			-0.143
			(1.89)
On-line Hours Since Last Overhaul			-0.178
			(0.62)
Calender Time Since Last Outage			0.170
			(1.79)
Number of Previous Outages [1]			0.237
			(0.92)
Number of Previous Maintenance Outages [1]			0.120
			(0.35)
Contra Costa 6- Previous to First Overhaul			-1.130
			(0.66)
Contra Costa 7- Previous to First Overhaul			-1.081
			(0.64)
Pittsburg 3- Previous to First Overhaul			-0.961
			(0.79)
Pittsburg 5- Previous to First Overhaul			-0.123
			(0.20)
Pittsburg 7- Previous to First Overhaul			0.659
			(0.79)
Petrero 3- Previous to First Overhaul			0.684
			(1.03)
Contra Costa 6		-0.969	-0.726
		(2.42)*	(1.33)
Contra Costa 7		-1.332	-1.074
		(3.59)**	(2.11)*
Pittsburg 1		-0.443	-0.379
		(1.10)	(0.62)
Pittsburg 2		-0.391	-0.360
		(0.96)	(0.58)
Pittsburg 3		-0.067	0.906
		(0.16)	(0.71)
Pittsburg 4		-0.554	-0.598
		(1.40)	(1.01)
Pittsburg 5		-0.704	-0.406
		(1.80)	(0.60)
Pittsburg 6		-0.966	-0.669
		(2.40)*	(1.24)
Pittsburg 7		-0.613	-0.422
		(1.48)	(0.77)
Constant	7.838	8.502	8.175
	(92.52)**	(27.91)**	(16.23)**
sigma	1.757	1.696	1.668
95% conf. Interval Upper	1.87	1.81	1.78
Lower	1.65	1.59	1.56
Crisis	-0.104	-0.232	-0.410
	(0.51)	(1.27)	(2.25)*

Absolute value of z statistics in parentheses
* significant at 5%; ** significant at 1%
(1) since last overhaul
Note: All variables have been scaled so that a value of 1 represents the mean value of the variable across the entire sample. Failures time measured in minutes.

Data Sources: Mirant Outage Data and the files CAL_SISO_4_Gen_Sch2_yyQ# containing data from the CD "ISO Responses to Cal Parties First Set of DR, EL00-95 et al, Disk 2."

APPENDIX

The Weibull failure law for the base hazard rate with shape parameter p and scale parameter β_0 yields

$$r_0(t) = pt^{p-1}e^{\beta_0}.$$
$$Let\ \lambda^p = e^{\beta_0}.$$
$$r_0(t) = pt^{p-1}\lambda^p,$$
$$R(t) = \int_0^t r_0(s)\,ds = t^p\lambda^p = (\lambda t)^p.$$
$$S(t) = e^{-R(t)} = e^{-(\lambda t)^p}.$$
$$f(t) = r(t)S(t) = \lambda p(\lambda t)^{p-1}\,e^{-(\lambda t)^p}.$$

Integrating by parts, we have the useful relation

$$\int_0^\infty xf(x)\,dx = \int_0^\infty x\,dF(x) = \int_0^\infty S(x)\,dx.$$

Hence, the expected time to failure is:

$$E(t) = \int_0^\infty S(x)\,dx = \int_0^\infty x\lambda p(\lambda x)^{p-1}\,e^{-(\lambda x)^p}\,dx.$$
$$= \frac{1}{\lambda}\int_0^\infty \lambda x e^{-(\lambda x)^p}\lambda p(\lambda x)^{p-1}\,dx.$$
$$= \frac{1}{\lambda}\int_0^\infty y^{\frac{1}{p}}e^{-y}\,dy = \frac{1}{\lambda}\Gamma\left(1+\frac{1}{p}\right).$$

In the case of several covariates fixed at the beginning of the period, the relation applies with the corresponding change in the scale parameter, $\lambda^p = e^{Z\beta}$.

With time varying covariates within the interval, calculation of the expected failure time requires numerical integration. In particular,

$$r(t) = pt^{p-1}e^{Z(t)\beta}.$$

$$R(t) = \int_0^t r(s)\,ds.$$

$$S(t) = e^{-R(t)}.$$

$$E(t) = \int_0^\infty xf(x)dx$$

$$= \int_0^\infty xr(x)e^{-R(x)}dx$$

$$= \int_0^\infty px^p e^{Z(x)\beta} e^{-\int_0^x ps^{p-1}e^{Z(s)\beta}ds} dx = \int_0^\infty S(x)\,dx = \int_0^\infty e^{-\int_0^x ps^{p-1}e^{Z(s)\beta}ds} dx.$$

In either representation, calculation of the expected time to failure requires in essence a double summation. We extended the summation until the survival function $S(t)$ was smaller than 0.0001.

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