

# BENCHMARKING THE OPERATING PERFORMANCE OF PORTLAND GENERAL ELECTRIC



**Pacific Economics Group Research, LLC**

# BENCHMARKING THE OPERATING PERFORMANCE OF PORTLAND GENERAL ELECTRIC

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# **1. INTRODUCTION AND SUMMARY**

## **1.1 Introduction**

Portland General Electric (“PGE” or “the Company”) is preparing to file for an increase in the base rates that recover the cost of its non-fuel inputs. Benchmarking is useful in assessing the reasonableness of its request. Managers use benchmarking today to gauge how well their companies are doing. Benchmarking also plays a growing role in regulation.

The personnel of Pacific Economics Group (“PEG”) Research LLC have extensive experience in utility performance research and incentive regulation, fields with a common foundation in economic statistics. Testimony quality benchmarking studies are a company specialty. We pioneered the use of scientific benchmarking methods in North American regulation. Company president and senior author Mark Newton Lowry has testified on benchmarking in numerous proceedings.

PGE has retained PEG Research to undertake an assessment of its recent operating performance. Separate studies were requested of non fuel operation and maintenance (“O&M”) expenses for generation and for distribution, customer care, and administration (“DCA”).<sup>1</sup> We have also been asked to benchmark the Company’s distribution reliability.

Following a brief summary of the work below, Chapter 2 provides an introduction to benchmarking and discusses our research methodology. Portland General Electric is described in Chapter 3. Our empirical research on DCA expenses is discussed in Chapter 4 and that for power generation expenses in Chapter 5. Chapter 6 provides a discussion of our reliability research. Some technical details of the research are presented in the Appendix.

## **1.2 Summary of Research**

Guided by economic theory, we developed mathematical models of the impact that various quantifiable business conditions have on the DCA and non-fuel generation O&M expenses of electric utilities. The parameters of the models, which measure cost impact, were estimated statistically using historical data on utility operations. Models fitted with

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<sup>1</sup> Power transmission expenses were excluded from the study because it is difficult to capture in a benchmarking study the oversized role that the Bonneville Power Administration plays in providing PGE with transmission services.

econometric parameter estimates and the business conditions that PGE faces were used as benchmarks. All estimates of the key model parameters were plausible and highly significant. We believe that this is the best practice approach to utility performance benchmarking given the data that are available in the United States today.

The econometric cost research was based on a sample of good quality data for 105 U.S. power distribution and 54 power generation utilities. The sample period was 1995 to 2008 for DCA and 2001-2007 for generation. The samples are large and varied enough to permit the development of highly credible cost models. The data used in model estimation were drawn from the Federal Energy Regulatory Commissions (“FERC”) Form 1 and other respected public sources. The DCA expenses of PGE were found to be about 11% below the benchmarks generated by the econometric model on average from 2006 to 2008. The Company’s non-fuel generation expenses were found to be about 5% below the benchmarks on average over the same period.

To benchmark the power reliability performance of PGE we used two metrics: the System Average Interruption Duration Index (“SAIDI”) and the System Average Interruption Frequency Index (“SAIFI”). We compared PGE’s reliability indices to benchmarks using econometric reliability models developed using standardized and publicly available data from 40 U.S utilities. These models quantified the impact of several business conditions on the reliability metrics. PGE’s SAIDI and SAIFI were found to be 67% and 48%, respectively below the benchmarks yielded by our econometric models on average from 2006 to 2008. Statistical tests revealed that these were significantly superior reliability performances.

## 2. AN INTRODUCTION TO BENCHMARKING

In this section of the report we introduce some important benchmarking concepts. The econometric benchmarking method used in the study is explained. More technical details of our methodology are discussed in the Appendix.

### 2.1 What is Benchmarking?

The word benchmark originally comes from the field of surveying. The *Oxford English Dictionary* defines a benchmark as

A surveyors mark, cut in some durable material, as a rock, wall, gate pillar, face of a building, etc. to indicate the starting, closing, ending or any suitable intermediate point in a line of levels for the determination of altitudes over the face of a country.

The term has subsequently been used more generally to indicate something that can be used as a point of comparison in performance appraisals.

A quantitative benchmarking exercise commonly involves one or more gauges of activity. These are sometimes called key performance indicators (“KPIs”). The value of each indicator achieved by an entity under scrutiny is compared to a benchmark value that reflects a performance standard. Given data on the cost of PGE and a certain cost benchmark we might, for instance, measure its cost performance by taking the ratio of the two values:

$$\text{Cost Performance} = \text{Cost}^{\text{PGE}} / \text{Cost}^{\text{Benchmark}}.$$

Benchmarks are often developed using data on the operations of agents that are involved in the activity under study. Statistical methods are useful in both the calculation of benchmarks and the comparison process. An approach to benchmarking that prominently features statistical methods is called statistical benchmarking.

Various performance standards can be used in benchmarking. These often reflect statistical concepts. One sensible standard is the average performance of the utilities in the sample.

## 2.2 External Business Conditions

For costs and many other kinds of KPIs, it is widely recognized that differences in the values of the indicators that companies achieve depend partly on differences in performance and partly on differences in the business conditions that they face. In cost research these conditions are sometimes called cost “drivers”.<sup>2</sup> The performance of a company depends on the KPI value that it achieves *given the business conditions that it faces*. Benchmarks must therefore reflect local business conditions if they are to embody a chosen performance standard faithfully.

Economic theory is useful in identifying cost drivers and controlling for their influence in benchmarking. We begin by positing that the actual cost incurred by a company is the product of the minimum achievable cost and an efficiency factor.<sup>3</sup> The goal of cost benchmarking is then to accurately estimate the efficiency factor.

Consider now that, under certain reasonable assumptions, cost functions exist that relate the minimum cost of an enterprise to business conditions in its service territory. When the focus of benchmarking is a subset of the entire series of inputs, cost theory shows that the minimum cost depends on the prices of the included inputs, output quantities, and on the amounts of other inputs that the company uses. This means that a fair appraisal of the efficiency with which a utility uses O&M inputs depends on the quantities of *capital* inputs that it owns.

Cost theory allows for the existence of *multiple* output variables in a cost function. This is important because it is often impossible to accurately measure the workload of a utility using only one output variable. The cost of power distribution may depend, for example, on the volume of power delivered as well as the number of customers served. It is also noteworthy that theory allows for the possibility that numerous business conditions other than input prices and output quantities can affect the minimum cost of service.

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<sup>2</sup> Business conditions that influence reliability indicators may, similarly, be called reliability drivers.

<sup>3</sup> Minimum achievable cost is a hypothetical notion and cannot be precisely calculated for specific utilities.



## 2.3 Econometric Benchmarking

### 2.3.1 Basic Assumptions

Relationships between the KPIs of utilities and the business conditions that they face can be estimated using statistics. A branch of statistics called econometrics has developed procedures for estimating the parameters of economic models using historical data.<sup>4</sup> The parameters of a cost function, for example, can be estimated using historical data on the costs incurred by a group of utilities and the business conditions that they faced. The sample used in model estimation can be a time series consisting of data over several years for a single company, a cross section consisting of one observation for each of several companies, or a “panel” data set that pools time series data for several companies.

Econometric research involves certain critical assumptions. The most important assumption, perhaps, is that the values of some economic variables (called dependent or left-hand side variables) are functions of certain other variables (called explanatory or right hand side variables) and error terms. In a cost model, cost is the dependent variable and the cost drivers are the explanatory variables. The explanatory variables are generally assumed to be independent in the sense that their values are not influenced by the values of dependent variables.

The error term in an econometric model for a KPI is the difference between the actual value of the indicator and the value predicted by the model. It reflects imperfections in the development of the model. The imperfections may include the mismeasurement of external business conditions, the exclusion from the model of relevant business conditions, and the failure of the model to capture the true form of the underlying functional relationship. Error terms are, in effect, a formal acknowledgement of the fact that the model is unlikely to provide a full explanation of the variation in the values of the KPIs for sampled utilities.

It is customary to assume that error terms are random variables with probability distributions that are determined by additional parameters, such as mean and variance, that can be estimated. This practice has several uses in econometric benchmarking. For example, tests can be constructed for the hypothesis that the parameter for a business

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<sup>4</sup> The act of estimating model parameters is sometimes called regression analysis.

condition variable under consideration for inclusion in a KPI model equals zero. A variable can be deemed a statistically significant cost driver if this hypothesis is rejected at a high level of confidence. In a benchmarking study used in utility regulation it is sensible to exclude from the model candidate business condition variables that do not have statistically significant parameter estimates, as well as those with implausible parameter estimates.

### 2.3.2 KPI Predictions and Performance Appraisals

A cost function fitted with econometric parameter estimates may be called an econometric cost model. A function for a reliability indicator such as SAIDI fitted with econometric parameter estimates may be called an econometric reliability model. We can use such models to predict a company's KPI values given local values for the business condition variables. These predictions are econometric benchmarks. KPI performance is measured in year  $t$  by comparing a company's KPI value in that year to the value projected for that year by the econometric model.<sup>5</sup>

### 2.3.3 Testing Efficiency Hypotheses

In econometric benchmarking, as in other approaches to benchmarking, there is naturally uncertainty about the accuracy of the “best guess” benchmark. One advantage of the econometric approach to benchmarking is that we can use econometric theory to identify a range of benchmark values, called a confidence interval, that encompasses the true benchmark value at a certain (*e.g.* 90%) confidence level. Confidence intervals developed from econometric results do more than provide us with indications of the accuracy of a benchmarking exercise. In particular, they permit us to test hypotheses regarding cost efficiency. Suppose, for example, that we use a sample average efficiency standard and compute the confidence interval for the benchmark that corresponds to the 90% confidence

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<sup>5</sup> Suppose, for example, that we wish to benchmark the distribution expenses of a hypothetical electric utility called Western Power. We might then predict the cost of Western in period  $t$  using the following model.

$$\hat{C}_{Western,t} = \hat{a}_0 + \hat{a}_1 \cdot N_{Western,t} + \hat{a}_2 \cdot W_{Western,t}.$$

Here  $\hat{C}_{Western,t}$  denotes the predicted cost of the company,  $N_{Western,t}$  is the number of customers it serves, and  $W_{Western,t}$  measures its wage rate. The  $\hat{a}_0$ ,  $\hat{a}_1$ , and  $\hat{a}_2$  terms are parameter estimates. Performance might then be measured using a formula such as

$$Performance = \left( \frac{C_{Western,t}}{\hat{C}_{Western,t}} \right).$$

level. It is then possible to test the hypothesis that the company has attained the benchmark standard of efficiency. If, for example, the company's actual cost exceeds the best guess benchmark generated by the model but nonetheless lies within the confidence interval this hypothesis cannot be rejected. In other words, the company is not a *significantly* inferior cost performer. Suppose, alternatively, that the company's cost is below the cost predicted by the model by enough to be outside the confidence interval. We may then conclude that it is a *significantly superior* cost performer.

An important advantage of efficiency hypothesis tests is that they take into account the accuracy of the benchmarking exercise. As we have tried to emphasize, there is uncertainty involved in the prediction of benchmarks. These uncertainties are properly reflected in the confidence interval that surrounds the point estimate (best single guess) of the benchmark value. The confidence interval will be greater the greater is the uncertainty regarding the true benchmark value. If uncertainty is great, our ability to draw conclusions about operating efficiency is hampered.

#### **2.3.4 Functional Form**

Econometric research requires the choice of a form for the functional relationship between a KPI and the business conditions that influence it. It is generally desirable to permit some flexibility in the form that is specified since the true form of the relationship between a KPI and the corresponding business conditions is usually unknown. We attempt to accomplish this by adding some quadratic terms (*e.g.* labor price x labor price) and interaction terms (*e.g.* labor price x delivery volume) to our models. The other terms in the model (*i.e.* those that are not quadratic or interaction terms) are called "first order" terms.

#### **2.3.5 Multiple Equation Cost Models**

Economic cost benchmarking is sometimes undertaken with multiple equation cost models. For example, non-fuel O&M expenses might be benchmarked with a model that consists of an O&M cost function and a *cost share* equation for labor that addresses the share of the expenses that is spent on labor.

A rigorous multiple equation approach to cost modeling that includes one or more share equations is generally preferable to the single equation approach. The chief advantage results from the fact that economic theory suggests that the parameters of the cost function

and share equations are linked. More data can thus be used in the estimation of cost model parameters. This increases the prospects for developing a cost benchmarking model that accurately reflects the effects of external business conditions. We have followed this approach in both cost studies described in this report.

### **3. AN INTRODUCTION TO PORTLAND GENERAL ELECTRIC**

PGE is a vertically integrated U.S. electric utility based in Portland, Oregon. Metropolitan Portland is the heart of its service territory. Service is provided, additionally, to numerous smaller towns outside the metro area that are located in the northern Willamette Valley. The company has about 800,000 retail customers. Residential and commercial customers account for the great bulk of retail demand.

The company has a remarkably diverse power supply mix. In 2008, self-generation accounted for only 66% of retail sales. Power is purchased from a diverse mix of vendors that consist primarily of publicly held hydro generators in the Pacific Northwest and a number of independent power producers.

About 43% of self-generation capacity is coal-fired. This includes the Boardman plant, a 1980 vintage facility located on the Columbia River near Umatilla, and the Colstrip plant, located in eastern Montana, which PGE co-owns with several other companies. About 41% of generated power is obtained from other fossil-fuel plants. These consist chiefly of gas-fired combined cycle units. The remaining 16% of PGE's generation output is obtained from hydroelectric facilities, which are located to the south and east of Portland in the Cascade Mountains. The largest of these is the Pelton-Round Butte facility near Madras on the eastern slope.

The Company owns and operates almost 1,600 miles of transmission line. The need for such lines is reduced by several circumstances. PGE has a compact service territory and most of the Company's own power generation is located fairly close to Portland. A substantial share of all purchased power, as well as power from the distant Colstrip plant, is delivered to the Company over transmission lines owned by the Bonneville Power Administration.

## **4. POWER DISTRIBUTION RESEARCH**

### **4.1 Data**

The primary sources of the cost and quantity data used in our empirical research for PGE were the Federal Energy Regulatory Commission (“FERC”) Form 1 and Form EIA 861 (“Annual Electric Utility Report”). Our data for both of these sources were gathered by SNL, a reputable commercial vendor. Major investor-owned electric utilities in the United States are required by law to file both forms annually. Data reported on the FERC Form 1 must conform to the FERC’s Uniform System of Accounts. Details of these accounts can be found in Title 18 of the Code of Federal Regulations.

Data were considered for inclusion in the sample from all major U.S. investor-owned electric utilities that filed the FERC Form 1 in 2008 and had substantial involvement in power distribution and customer care.<sup>6</sup> To be included in the study the data were required, additionally, to be plausible and not unduly burdensome to process. Data from 105 companies were used in the power distribution research. These companies are listed in Table 1. The sample period was 1995-2008. The resultant data set has 1,446 observations.<sup>7</sup> This sample is large and varied enough to permit econometric identification of numerous O&M cost drivers and reasonably accurate estimation of their cost impact.

Other sources of data were also accessed in the research. Some of these sources are used to measure input prices, and included the Bureau of Labor Statistics (“BLS”) of the U.S. Department of Labor for labor prices and Global Insight for electric utility material and service (“M&S”) prices. Data on weather related variables and the number of gas customers served were obtained from the National Climatic Data Center and gas distributor filings to state Commissions, respectively.

### **4.2 Definition of Variables**

#### **4.2.1 Cost**

Cost figures play a key role in our research for PGE. The expenses used in the DCA benchmarking work are reported O&M expenses for distribution, customer accounts,

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<sup>6</sup> We excluded from the sample some utilities that were primarily engaged in power generation or transmission.

<sup>7</sup> Some observations for companies with data included in the sample were excluded due to data problems.

Table 1

## SAMPLE OF UTILITIES IN THE DCA COST RESEARCH

Alabama Power	Metropolitan Edison
AmerenUE	MidAmerican Energy
Appalachian Power	Minnesota Power
Arizona Public Service	Monongahela Power
Atlantic City Electric	MDU Resources Group
Avista	Narragansett Electric
Baltimore Gas and Electric	Nevada Power
Bangor Hydro-Electric	Northern Indiana Public Service
Black Hills Power	Northern States Power - MN
Carolina Power & Light	Northern States Power - WI
Central Hudson Gas & Electric	Ohio Edison
Central Illinois Light	Ohio Power
Central Illinois Public Service	Oklahoma Gas and Electric
Central Maine Power	Orange and Rockland Utilities
Central Vermont Public Service	Otter Tail
Cleco Power	Pacific Gas and Electric
Cleveland Electric Illuminating	PacifiCorp
Columbus Southern Power	PECO Energy
Commonwealth Edison	Pennsylvania Electric
Connecticut Light and Power	Pennsylvania Power
Consolidated Edison	Pennsylvania Power & Light
Consumers Energy	Portland General Electric
Dayton Power and Light	Potomac Edison
Delmarva Power & Light	Potomac Electric Power
Detroit Edison	Public Service Company of Colorado
Duke Energy Carolinas	Public Service Company of New Hampshire
Duke Energy Indiana	Public Service Company of New Mexico
Duke Energy Ohio	Public Service Company of Oklahoma
Edison Sault Electric	Public Service Electric and Gas
El Paso Electric	Puget Sound Energy
Empire District Electric	Rochester Gas & Electric
Entergy Arkansas	San Diego Gas & Electric
Entergy Mississippi	Sierra Pacific Power
Fitchburg Gas and Electric Light	South Carolina Electric & Gas
Florida Power & Light	Southern California Edison
Florida Power	Southern Indiana Gas and Electric
Georgia Power	Southwestern Electric Power
Green Mountain Power	Southwestern Public Service
Gulf Power	Superior Water, Light and Power
Idaho Power	Tampa Electric
Illinois Power	Toledo Edison
Indiana Michigan Power	Tucson Electric Power
Indianapolis Power & Light	United Illuminating
Kansas City Power & Light	Upper Peninsula Power
Kansas Gas and Electric	Virginia Electric Power
Kentucky Power	West Penn Power
Kentucky Utilities	Western Massachusetts Electric
Kingsport Power	Westar Energy
Lockhart Power	Wheeling Power
Louisville Gas and Electric	Wisconsin Electric Power
Madison Gas and Electric	Wisconsin Power & Light
Maine Public Service	Wisconsin Public Service
Massachusetts Electric	

105 sampled utilities

customer service and information, sales, and administration less franchise fees and expenses for pensions and benefits. We routinely exclude pension and benefit expenses from our cost benchmarking work on the grounds that they are volatile, vary with accounting practices, and are to a considerable degree beyond the control of utility management.

#### **4.2.2 Output Measures**

Two output measures are used in the DCA cost model. One is the annual average number of customers served. The other is the megawatt hours of residential and commercial retail deliveries.<sup>8</sup>

#### **4.2.3 Input Prices**

Cost theory also suggests that the prices paid for production inputs are relevant business condition variables. In this model, we have specified price indexes for labor and M&S inputs.<sup>9</sup> We expect cost to be higher the higher are the values of both indexes.

The labor price index used in this study is constructed by PEG Research personnel using BLS data. Occupational Employment Statistics (“OES”) data for 2008 are used to construct wage rate comparisons for each utility’s service territory. An average wage comparison is calculated using cost share weights that correspond to the electric utility industry for the U.S. as a whole. Values for other years are calculated by adjusting the index level in the focus year for changes in regionalized BLS indexes of employment cost trends in the utility sector.

Prices for material and service (“M&S”) O&M inputs are assumed to have a 25% local labor content and therefore tend to be a little higher in regions with higher labor prices. They are escalated by a summary M&S input price index constructed by PEG Research from detailed Global Insight electric utility M&S indexes.

#### **4.2.4 Other Business Conditions**

Seven other business condition variables are included in the DCA cost model. These variables measure conditions that affect the cost of providing DCA services. One of these variables measures the extent of system overheading. System overheading involves higher

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<sup>8</sup> Industrial and other retail deliveries are excluded because they tend to have considerably less cost impact per MWh.

<sup>9</sup> Cost is divided by the M&S input price so that this variable does not appear explicitly in the model.



O&M expenses over the years because lines are more exposed to the challenges posed by local weather (*e.g.* high winds and ice storms), flora, and fauna<sup>10</sup>. The variable used to capture the extent of overheading is the share of overhead distribution plant in the total gross value of overhead and underground plant. The FERC Form 1 is the source of the plant value data.

A second additional business condition variable is a measure of the demand side management (“DSM”) work being done by each utility. Due to a lack of explicit itemization of DSM expenses on the FERC Form 1, these expenses are difficult to remove from the costs subject to benchmarking. A control variable is therefore needed and we use for this purpose the share of customer service and information (“CS&I”) expenses in the total distribution, customer account, and CS&I expenses on FERC Form 1. This approach makes sense because DSM expenses are usually reported as a CS&I expense and loom large in these expenses when DSM programs are large. Given this, we would expect that the higher the value of the variable the higher DCA cost would be. We expect the corresponding parameter estimate to have a positive sign.

The third added business condition variable is the number of customers for which a utility provides gas service. Simultaneous provision of delivery and customer care services to gas and electric customers involves opportunities to share inputs that economists call economies of scope. We therefore expect a utility’s reported electric O&M expenses to be lower the higher is the number of gas customers served. The parameter estimate should have a negative sign.

The average heating degree days in each utility’s service territory is the fourth additional business condition variable in the model. This variable captures the cost associated with operating under severe winter weather conditions. We expect the corresponding parameter estimate to be positive.

The company’s net generation volume is the fifth business condition variable. This variable was included to capture the extra administrative costs of running a generation operation. We expect the parameter estimate for this variable to have a positive sign.

A sixth added variable is the average precipitation in the service territory. This serves as a proxy for forestation, which raises distributor O&M cost due to tree trimming

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<sup>10</sup> Maintenance of underground distribution facilities occurs less frequently but can be quite costly.

and maintenance activities. Thus, we expect the parameter estimate corresponding to this variable to be positive.

The econometric model also contains a trend variable. This permits predicted cost to shift over time for reasons other than changes in the specified business conditions. The trend variable captures the net effect on cost of diverse conditions, such as technological change, that are otherwise excluded from the model. Parameters for such variables typically have a negative sign in statistical cost research.

### **4.3 Parameter Estimates**

Estimation results for the cost model are reported in Table 2. In this and the other three tables that present econometric results, we shade results for first order terms for reader convenience. These tables also report the values of the t-ratios that correspond to each parameter estimate. A parameter estimate is deemed statistically significant if the hypothesis that the true parameter value equals zero is rejected. This statistical test requires the selection of a critical value for the t ratio. In this study, we employed a critical value that is appropriate for a 90% confidence level given a large sample. The value of the t-ratio corresponding to this confidence level is about 1.6. The t-ratios are used in model specification. All first order terms were required to have statistically significant and sensibly-signed parameter estimates.

Table 2 and the other tables of econometric results also report p values. These are alternative indicators of the statistical significance of parameter estimates. A parameter estimate that is significant at no more than a 90% confidence level has a p value of 0.10.

Examining the results in Table 2, it can be seen that all of the parameter estimates for first order terms are statistically significant and plausible as to sign and magnitude. At the sample mean, cost was found to be higher the higher were the values of the two scale-related variables. A 1% increase in the number of customers served is estimated to raise O&M expenses by 0.82%. A 1% hike in the residential and commercial delivered volume is estimated to raise cost by 0.13% in the long run. Thus, the number of customers served is

Table 2

## Econometric Model of Distribution, Customer Care, and Administrative O&M Expenses

### VARIABLE KEY

WL = Labor Price  
 N = Number of Customers  
 VRC = Residential & Commercial Delivery Volume  
 DSM = Share of CS&I in Distribution and Customer Care O&M  
 POH = Percent of Distribution Plant Overhead  
 NG = Number of Gas Customers  
 G = Net Generation  
 HDD = Average Heating Degree Days  
 P = Average Precipitation  
 Trend = Time Trend

COST DRIVER	PARAMETER ESTIMATE	T-STATISTIC	P-VALUE
<b>WL</b>	0.360	108.99	0.000
WLWL	0.093	2.41	0.016
WLN	-0.009	-0.69	0.489
WLVRC	-0.012	-1.03	0.305
<b>N</b>	0.817	31.06	0.000
NN	0.381	2.88	0.004
NVRC	-0.387	-3.12	0.002
<b>VRC</b>	0.128	4.80	0.000
VRCVRC	0.377	3.17	0.002

COST DRIVER	PARAMETER ESTIMATE	T-STATISTIC	P-VALUE
<b>DSM</b>	0.028	6.742	0.000
<b>POH</b>	0.144	7.732	0.000
<b>NG</b>	-0.003	-2.609	0.009
<b>G</b>	0.059	7.152	0.000
<b>HDD</b>	0.009	10.075	0.000
<b>P</b>	0.019	1.848	0.065
Trend	-0.015	-13.893	0.000
Constant	12.300	918.586	0.000
System Rbar-Squared	0.969		
Sample Period	1995-2008		
Number of Observatio	1446		

the chief output related driver of DCA expenses. Cost was also higher the higher was the labor price.

The parameter estimates for the additional business condition variables were also sensible. DCA O&M expenses are

- higher the higher is the apparent amount of DSM work undertaken;
- higher the greater is the extent of distribution system overhauling;
- lower the larger is the number of gas customers served;
- higher the greater is the winter weather severity;
- higher the more generation work a utility undertakes; and
- higher the greater is the amount of precipitation.

The estimate of the trend variable parameter suggests a 1.5% annual downward shift in cost for reasons other than the trends in the included business condition variables.

The table also reports the system- $R^2$  statistic for the model. This is a widely used measure of the ability of the model to explain variation in the sampled costs of distributors. Its value is about 0.97, suggesting that the explanatory power of the model was high.

#### **4.4 Business Conditions of PGE**

Table 3 compares the average values of the business conditions that PGE faced over the 2006-2008 period to the average values for the full DCA cost sample. It can be seen that the company's DCA O&M expenses were only 0.91 times the sample mean. The number of customers served was, meanwhile, 0.96 times the mean, while residential and commercial deliveries were 0.95 times the mean and the net generation volume was 0.67 times the mean. Regarding input prices, the table shows that the labor prices faced by PGE were about 1.12 times the sample mean and the M&S price index was 1.03 times the mean.

As for the other business condition variables, DSM programs are administered by an independent agency in Oregon, so the share of CS&I was only 0.59 times the mean. The percentage of plant that is overhead was 0.89 times the mean. This is a reflection of the company's substantially urbanized service territory. There are no gas customers to provide opportunities for scope economies. Average precipitation was 0.98 times the mean, whereas the average heating degree days was 0.84 times the mean.

Table 3

### Comparison of PGE's Distribution, Customer Care and A&G Business Conditions To Full Sample Norms

Business Condition	Units	Mean Values 2006-2008		PGE Mean/Sample Mean
		PGE	Full Sample	
Distribution, Customer Care and Administrative O&M Cost	Dollars ('000)	210,311	230,404	0.91
Retail Customers	Count	800,324	837,134	0.96
Residential and Commercial Retail Deliveries	MWh	15,200,311	15,987,694	0.95
Net Generation	MWh	9,757,415	14,636,447	0.67
Labor Price	Index Number	0.938	0.840	1.12
Other O&M Input Price	Index Number	1.239	1.205	1.03
Percent Customer Service and Information Expenses	Percent	0.071	0.120	0.59
Percent of Distribution Plant that is Overhead	Percent	0.564	0.632	0.89
Gas Customers	Count	0	183,721	0.00
Average Precipitation	Inches	35.889	36.704	0.98
Heating Degree Days	Degree Days	4,239	5,036	0.84

## **4.5 Benchmarking Results**

Table 4 presents the results of our econometric appraisal of PGE's average DCA O&M expenses for the 2006-2008 period. The company's cost was about 11% below the model's prediction on average. However, we cannot reject the hypothesis, at the 90% confidence level, that the company was an average DCA cost performer over this period.

Table 4

## **Comparison of Actual and Predicted DCA Expenses for PGE**

<u>Year</u>	<u>Difference (%)</u>
2006	-15.7%
2007	-10.9%
2008	-7.2%
2006-2008 Average	-11.2%

## **5. POWER GENERATION RESEARCH**

### **5.1 Data**

The primary source of the cost and output data used in our research on power generation cost is the FERC Form 1. Other sources of data were also accessed in the power generation research. Data on generation capacity originated in Form EIA – 860 (“Annual Electric Generator Report”) and a predecessor data source, Form EIA – 767 (“Annual Steam Electric Plant Operation and Design Report”). We once again rely on SNL compilations. The input price data were obtained from the same sources mentioned in the power distribution section.

Data from 54 companies were used in the power generation research. The sample is smaller than that used in the DCA cost research because many U.S. utilities that provide distribution services have restructured and no longer provide generation services. The companies included in the sample are listed in Table 5. The sample period for model estimation was 2001-2007.<sup>11</sup> The resultant data set has 374 observations.<sup>12</sup> This sample is large and varied enough to permit econometric identification of several generation cost drivers and reasonably accurate estimation of their likely cost impact.

### **5.2 Definition of Variables**

#### **5.2.1 Cost and Output Measures**

The generation cost addressed in our study is total power production O&M expenses less fuel and purchased power expenses. In addition to Purchased Power expenses as reported on the FERC Form 1, we also exclude the Other Expenses category of Other Power Supply Expenses. We believe that large and volatile costs that are often commodity-related are sometimes reported in this category. One output measure is used in the generation O&M cost model: the total annual megawatt hours of net generation.

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<sup>11</sup> We have less confidence in some of the SNL capacity data before 2001. The requisite capacity data for 2008 are not yet available for all sampled companies.

<sup>12</sup> Some observations for companies in the sample were excluded due to data problems.



Table 5

## **SAMPLE OF UTILITIES IN GENERATION COST RESEARCH**

Alabama Power	MidAmerican Energy
AmerenUE	Minnesota Power
Appalachian Power	Mississippi Power
Arizona Public Service	Montana Dakota Utilities
Avista	Nevada Power
Black Hills Power	Northern Indiana Public Service
Carolina Power & Light	Northern States Power - MN
Cleco Power	Ohio Power
Columbus Southern Power	Oklahoma Gas and Electric
Consumers Energy	Otter Tail Corporation
Dayton Power and Light	PacifiCorp
Detroit Edison	Portland General Electric
Duke Energy Carolinas	Public Service Company of Colorado
Empire District Electric	Public Service Company of New Hampshire
Entergy Mississippi	Public Service Company of New Mexico
Florida Power & Light	Public Service Company of Oklahoma
Florida Power Corporation	Puget Sound Energy
Georgia Power	Sierra Pacific Power
Gulf Power	South Carolina Electric & Gas
Idaho Power	Southern Indiana Gas and Electric
Indiana Michigan Power	Southwestern Electric Power
Indianapolis Power & Light	Southwestern Public Service
Kansas City Power & Light	Tampa Electric
Kentucky Power	Virginia Electric and Power
Kentucky Utilities	Westar Energy (KPL)
Louisville Gas and Electric	Wisconsin Power and Light
Madison Gas and Electric	Wisconsin Public Service

54 sampled utilities

### 5.2.2 Input Prices

As discussed in Chapter 4, cost theory suggests that the prices paid for production inputs are relevant business condition variables. We include price indexes for two kinds of inputs in the model. The labor price index is the same as that discussed in Chapter 4. The M&S input price index was calculated using data on prices of generation M&S inputs from Global Insight.<sup>13</sup> Like its DCA counterpart, we assume a 25% local labor content for this index so that its value is a little higher in areas of higher salaries and wages.

### 5.2.3 Other Business Conditions

Five other business condition variables are included in the generation cost model. One is the total generation capacity. Capacity is an important supplemental cost driver because the non-fuel O&M expenses associated with it can be substantial even when it is idle. Data on capacity are processed from EIA 860 data on individual power plants. Our research team aggregated the nameplate capacity of each sampled utility's power plants to arrive at a total capacity figure. We expect that O&M expenses will be higher the higher is the amount of generation capacity. The parameter estimate should therefore have a positive sign.

Two other business condition variables included in the model are the shares of generating capacity owned by each company that are coal-fired and nuclear-fueled. These variables are designed to capture any tendency for O&M expenses to vary with the kind of generating plant that companies own. We expect the parameter estimates corresponding to both variables to have positive signs.

The fourth business condition variable in the model is the percentage of capacity that is scrubbed for sulfur. Cost should be higher the higher is this share. We therefore expect the corresponding parameter estimate to be positive. The econometric model also contains a trend variable. We have noted that the parameters for such variables typically have a negative sign in statistical cost research.

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<sup>13</sup> Cost is divided by the generation M&S price so that it does not appear as a right hand side variable in the model.

## 5.3 Parameter Estimates

Estimation results for the cost model are reported in Table 6. Examining the results, it can be seen that all of the model parameter estimates for first order terms are statistically significant and plausible as to sign and magnitude. At sample mean values of the business condition variables, a 1% hike in the generation volume was estimated to raise cost 0.36%. A 1% increase in generation capacity was estimated to raise cost 0.48%. Here are the results for the other business condition variables.

- Cost was higher the greater was the labor price.
- Cost was higher the greater were the percentages of capacity that were coal-fired or nuclear.
- Cost was also higher the greater was the percentage of capacity that was scrubbed for SO<sub>2</sub>.
- The estimate of the trend variable parameter suggests a 1.1% annual increase in cost over time for reasons other than the trends in the business condition variables.

The table also reports the system  $R^2$  statistic for the model. This is a widely used measure of the ability of the model to explain variation in the sampled costs of distributors. Its value was about 0.95, suggesting that the explanatory power of the model was high.

## 5.4 Business Conditions of PGE

Table 7 compares the average values of the generation business conditions that PGE faced from 2005 to 2007 to the average values for the sample. It can be seen that the company's generation O&M expenses were only 0.31 times the sample mean. The net generation volume was 0.34 times the mean, while the generation capacity was 0.40 times the mean. The table also shows that the labor price faced by PGE was about 1.15 times the sample mean.<sup>14</sup>

Turning to the additional business conditions, PGE had no nuclear capacity. The share of its generation capacity that was coal-fired capacity was only 0.61 times the mean. The share of capacity that was scrubbed for sulfur was only 0.71 times the mean.

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<sup>14</sup> This comparison differs from that in the DCA sample because that sample includes a number of utilities in California and the northeast and north central U.S.

Table 6

# Econometric Model of Non-Fuel Generation O&M Expenses

## VARIABLE KEY

WL = Labor Price  
 YG = Net Generation Volume  
 KG = Total Generation Capacity  
 PCN = % of Capacity Nuclear  
 PCC = % of Capacity Coal  
 PCS = % of Capacity that is Scrubbed  
 Trend = Time Trend

COST DRIVER	PARAMETER ESTIMATE	T-STATISTIC	P-VALUE
<b>WL</b>	0.370	76.73	0.000
WLWL	0.091	1.54	0.125
WLYG	-0.014	-0.86	0.389
WLKG	0.044	2.63	0.009
<b>YG</b>	0.360	7.50	0.000
YGYG	-0.253	-1.72	0.086
YGKG	0.262	1.69	0.092
<b>KG</b>	0.477	9.68	0.000
KGKG	-0.241	-1.40	0.162

COST DRIVER	PARAMETER ESTIMATE	T-STATISTIC	P-VALUE
<b>PCN</b>	0.187	24.35	0.000
<b>PCC</b>	0.197	8.44	0.000
<b>PCS</b>	0.019	2.14	0.033
Trend	0.011	3.77	0.000
Constant	11.053	267.39	0.000
System Rbar-Squared	0.946		
Sample Period	2001-2007		
Number of Observations	374		

Table 7

## Comparison of PGE's Generation Business Conditions To Full Sample Norms

Business Condition	Units	Mean Values 2005-2007		PGE Mean/Sample Mean
		PGE	Full Sample	
Generation O&M Cost	Dollars ('000)	56,114	178,362	0.31
Net Generation	MWh	8,477,820	24,634,374	0.34
Total Capacity	MW	2,247	5,551	0.40
Labor Price	Index	0.908	0.790	1.15
Other O&M Input Price	Index	1.495	1.441	1.04
Percent Capacity Nuclear	Percent	0	0.058	0.00
Percent Capacity Coal	Percent	0.325	0.533	0.61
Percent of Total Capacity that is Scrubbed	Percent	0.141	0.200	0.71

## **5.5 Benchmarking Results**

Table 8 presents the results of our econometric appraisal of PGE's generation O&M expenses for the 2006-2008 period. The Company's expenses were found to be about 5% below the model's projection on average. We cannot, at a 90% confidence level, reject the hypothesis that the company was an average cost performer.

Table 8

## Comparison of Actual and Predicted Generation Expenses for PGE

<u>Year</u>	<u>Difference (%)</u>
2006	0.7%
2007	-10.0%
2008	-5.9%
2006-2008 Average	-5.1%

## 6. RELIABILITY RESEARCH

We discuss our benchmarking study of the reliability of power distribution service in this section. We start by looking at the measures of distribution reliability followed by the data used in the study. We then present our benchmarking models used to assess PGE's performance.

### 6.1 Definitions

There are many dimensions of service quality in power distribution. Our focus here is on reliability of power delivery to electric end-users as measured by service continuity and, in case of disruption, rapid restoration of service. Continuous access to electric power is essential to the functioning of modern homes and businesses. The essential nature of power demand makes interruptions in power delivery costly to customers. Power distribution utilities are therefore expected to design and operate distribution networks to assure reliable deliveries. Even well-run delivery systems are, however, subject to disruption from accidents and weather conditions. When disruptions occur, distribution companies are expected to restore service promptly.

The specific indicators that utilities use to gauge reliability vary somewhat from company to company, but there are broad similarities among the types of performance indicators used for this purpose. These metrics gauge mostly the frequency and duration of power interruptions. The two most typical measures used in utility regulation are:

- SAIDI, the number of minutes of sustained power interruptions that is experienced annually by an average customer on the system
- SAIFI, the number of sustained interruptions that is experienced annually by an average customer on the system

Public utility commissions in some jurisdictions mandate reliability standards based on these indices. The definition of “sustained” outages and events that can be excluded from index calculations, called major event days (“MEDs”), vary. In order to ensure comparability of SAIDI and SAIFI definitions used in our study, we collected and used only indices that reflect standards set up by the Institute of Electrical and Electronic Engineers (“IEEE”). In its “Guide for Electric Distribution Reliability Indices,” standard number P1366, the IEEE



sets up definitions of sustained outages and MEDs. Sustained outages are those that last at least five minutes and MEDs are based on what it calls the beta method. This method sets up threshold values, only above which outages are recorded, based on log averages and standard deviations of daily outage data for the past five years for each utility. Essentially, an MED is based on the experience of each utility standardized in the same way, and permits the smoothing of reliability data that can be affected by extraordinary and severe weather conditions.

## **6.2 Data**

There are two primary sources for the IEEE standard based reliability indices used in this study. The first is public utility commissions that monitor reliability as part of their regulatory activities and make information available either on their website or upon request. The second main source of these data is utilities that for other reasons collect reliability information and calculate indices using the IEEE definitions. We were able to collect data from 40 major electric utilities. The list of these utilities is given in Table 9. The sample is large and varied enough to permit the identification of several reliability drivers. These utilities had IEEE based reliability data for differing years, the most comprehensive being the years 1998-2008 while the most typical was the years 2003-2008. Ultimately, the dataset used to benchmark reliability performance had 248 observations. The sources for the other data used in our reliability benchmarking research are the same ones detailed in the DCA cost benchmarking section.

## **6.3 Reliability Benchmarking Models**

We developed reliability benchmarking models for both SAIDI and SAIFI. The SAIDI model explains system average outage duration using customer density (as measured by the number of customers per distribution line mile), percent plant overhead, forestation, precipitation, heating degree days, and a trend variable. The SAIFI model includes all of the above variables, except plant overhead, and uses cooling degree days instead of heating

Table 9

## **SAMPLE OF UTILITIES USED IN RELIABILITY RESEARCH**

Avista	Northern States Power - Minnesota
Baltimore Gas & Electric	Ohio Edison
Bangor Hydro-Electric	Ohio Power
Central Maine Power	Oklahoma Gas and Electric
Cincinnati Gas & Electric	Otter Tail Power
Cleveland Electric Illuminating	Pacific Gas and Electric
Columbus Southern Power	Pennsylvania Electric
Commonwealth Edison	Pennsylvania Power
Dayton Power & Light	Portland General Electric
Duquesne Light	Potomac Electric Power
Georgia Power	PSI Energy Inc
Indianapolis Power & Light	Public Service Company of Colorado
Kansas City Power & Light	Public Service Company of New Mexico
Kentucky Power	Public Service Company of Oklahoma
Kentucky Utilities	Puget Sound Energy
Louisville Gas and Electric	Southern California Edison
Maine Public Service	Southern Indiana Gas and Electric
Metropolitan Edison	Toledo Edison
Minnesota Power	Union Light Heat & Power
Northern Indiana Public Service	West Penn Power

40 sampled utilities

degree days as explanatory variables. In addition, a quadratic (*i.e.* “squared”) term of the number of customers is featured in both models.<sup>15</sup>

The econometric results for the SAIDI model are presented in Table 10 and those for the SAIFI in Table 11. Inspecting the results in Table 10, it can be seen that the higher the density the shorter was the SAIDI, while overhead plant, forestation, and precipitation increased outage duration. We also note a 0.2% annual increase in SAIDI over the sample period for reasons other than trends in the included business condition variables. We can observe similar estimates in the SAIFI model. Inspecting the results in Table 11 we find that SAIFI was lower with greater customer density, but higher with more forestation, precipitation, and cooling degree days, which is a proxy for the severity of summer heat. The parameter estimate of the trend term in this model indicates a 1.0% annual decline in outage frequency. In both models, the parameter estimates for most of the quadratic terms are significant, suggesting the desirability of flexible functional forms for reliability modeling.

Table 12 presents a comparison of the average values of SAIDI, SAIFI and all right hand side variables used in the models for the 2006 – 2008 period. The SAIDI and SAIFI values experienced by PGE were 49% and 58%, respectively, of the sample means. In addition, compared to the sample average over the same period PGE

- had 19% more customer density;
- had 10% less overhead plant;
- had 57% more forestation;
- had 58% less cooling degree days;
- had 4% less precipitation; and
- served 14% fewer customers.

## 6.4 Benchmarking Results

Tables 13 and 14 present the results of our econometric appraisal of PGE’s SAIDI and SAIFI, respectively, for the 2006-2008 period. PGE’s SAIDI value was 67% below its

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<sup>15</sup> Recall that the SAIDI and SAIFI metrics already include the number of customers served in the denominator.

Table 10

# Econometric Model of SAIDI

## VARIABLE KEY

NMD Customers per Distribution Line Mile

POH % Distribution Plant Overhead

PF % of Forestation

P Average Precipitation

N Number of Customers

RELIABILITY DRIVER	PARAMETER ESTIMATE	T-STATISTIC	P-VALUE
<b>NMD</b>	-0.255	-5.003	0.000
NMDNMD	-0.368	-3.057	0.002
<b>POH</b>	0.485	6.362	0.000
POHPOH	1.019	7.034	0.000

RELIABILITY DRIVER	PARAMETER ESTIMATE	T-STATISTIC	P-VALUE
<b>PF</b>	0.222	7.388	0.000
PFPF	0.037	1.679	0.094
<b>P</b>	0.192	3.969	0.000
PP	-0.108	-2.039	0.043
NN	-0.031	-3.569	0.000

<b>Trend</b>	0.002	0.337	0.737
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Constant	4.866	88.989	0.000
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Sample Period	Varies, typically 2003-2008
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Rbar-Squared	0.352
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Number of Observations	248
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Table 11

# Econometric Model of SAIFI

## VARIABLE KEY

NMD	Customers per Distribution Line Mile
PF	% of Forestation
CDD	Cooling Degree Days
P	Average Precipitation
N	Number of Customers

PARAMETER			
COST DRIVER	ESTIMATE	T-STATISTIC	P-VALUE
<b>NMD</b>	-0.152	-3.975	0.000
NMDNMD	-0.067	-0.709	0.479
<b>PF</b>	0.255	8.932	0.000
PFPF	0.104	5.280	0.000

PARAMETER			
COST DRIVER	ESTIMATE	T-STATISTIC	P-VALUE
<b>CDD</b>	0.097	3.525	0.001
CDDCDD	-0.033	-1.805	0.072
<b>P</b>	0.232	5.015	0.000
PP	0.081	2.029	0.044
NN	0.034	4.286	0.000
<b>Trend</b>	-0.010	-2.079	0.039

Sample Period                      Varies, typically 2003-2008

Number of Observations        248

Constant                            0.217                      4.732                      0.000

Rbar-Squared                      0.394

Table 12

## Comparison of PGE's Reliability Variables To Full Sample Norms

Business Condition	Units	Mean Values 2006-2008		PGE Mean/Sample Mean
		PGE	Full Sample	
SAIDI	Minutes	71.835	147.448	0.49
SAIFI	Count	0.727	1.264	0.58
Customers per Distribution Line Mile	Ratio	45.228	37.956	1.19
Percent Distribution Plant Overhead	Percent	0.56	0.63	0.90
Percent of Service Territory that is Forested	Percent	0.63	0.40	1.57
Cooling Degree Days	Degree Days	465	1103	0.42
Precipitation	Inches	37.37	38.75	0.96
Number of Customers	Count	800,324	925,436	0.86

Table 13

## Comparison of Actual and Predicted SAIDI for PGE

<u>Year</u>	<u>Difference (%)</u>
2006	-68.8%
2007	-72.1%
2008	-61.1%
2006-2008 Average	-67.4%

Table 14

## Comparison of Actual and Predicted SAIFI for PGE

<u>Year</u>	<u>Difference (%)</u>
2006	-46.7%
2007	-53.0%
2008	-43.0%
2006-2008 Average	-47.6%



benchmark on average over the last three years of the sample, 2006-2008, while its average SAIFI value was about 48% below its benchmark over the same time period. We rejected, at a 90% confidence level, the hypotheses that PGE was an average SAIDI and SAIFI performer during these years. We conclude instead that PGE was a significantly superior reliability performer.

## APPENDIX

This section provides additional and more technical details of our empirical research.

### Form of the Model

Specific forms must be chosen for functions used in econometric research. Forms commonly employed by scholars include the linear, the double log and the translog. Here is a simple example of a linear cost model. For each company  $h$  in year  $t$ ,

$$C_{h,t} = a_0 + a_1 \cdot N_{h,t} + a_2 \cdot W_{h,t}^{16} \quad [A1]$$

Here is an analogous cost model of double log form.

$$\ln C_{h,t} = a_0 + a_1 \cdot \ln N_{h,t} + a_2 \cdot \ln W_{h,t} \quad [A2]$$

The expression “ln” here indicates a natural logarithm. In a double log model the values of the dependent variable and both business condition variables are logged. This specification has the effect of making the parameter corresponding to each business condition variable the elasticity of cost with respect to the variable. For example, the  $a_1$  parameter indicates the % change in cost resulting from 1% growth in the number of customers. Elasticity estimates are informative and make it easier to assess the reasonableness of model results. It is also noteworthy that, in a double log model, the elasticities are *constant* in the sense that they are the same for every value that the KPI and the corresponding business condition variables might assume.<sup>17</sup> This is restrictive, and may be inconsistent with the true form of the relationship that we are trying to model.

Here is an analogous cost model of translog form

$$\begin{aligned} \ln C_{h,t} = & a_0 + a_1 \cdot \ln N_{h,t} + a_2 \cdot \ln W_{h,t} + a_3 \cdot \ln N_{h,t} \cdot \ln N_{h,t} \\ & + a_4 \cdot \ln W_{h,t} \cdot \ln W_{h,t} + a_5 \cdot \ln W_{h,t} \cdot \ln N_{h,t} \end{aligned} \quad [A3]$$

This form differs from the double log form in the addition of quadratic and interaction terms. Quadratic terms such as  $\ln N_{h,t} \cdot \ln N_{h,t}$  permit the elasticity of cost with respect to each business condition variable to differ at different values of the variable. The elasticity of cost with respect to the output variable may, for example, be lower for a small utility than

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<sup>16</sup> The terms in this model were defined in the footnote on page 8.

<sup>17</sup> Cost elasticities are not constant in the linear model that is exemplified by equation [A1].

for a large utility that has exhausted its opportunities to realize incremental scale economies. Interaction terms like  $\ln W_{h,t} \cdot \ln N_{h,t}$  permit the elasticity of cost with respect to one business condition variable to depend on the value of another such variable. For example, the elasticity of cost with respect to growth in the number of customers served may depend on the price of labor in the service territory.

The translog form is an example of “flexible” functional form. Flexible forms can accommodate a greater variety of possible relationships between KPIs and the business condition variables. A disadvantage of the translog form is that it involves many more variables than simpler forms such as the double log. As the number of variables subject to the translog treatment increases, the precision of a model’s parameter estimates falls. It is therefore common to limit the number of variables in a cost model that are translogged.

In this study, we have tried to strike a balance between the flexibility of the functional forms and the desire for statistically significant parameter estimates. We do this by limiting the translog treatment to variables that are predicted to be cost drivers in economic theory. Most other variables are simply logged.<sup>18</sup>

### **Estimation Procedure**

A variety of estimation procedures are used in econometric research. The appropriateness of each procedure depends on the assumptions that are made about the distribution of the error terms. The estimation procedure that is most widely known, ordinary least squares (“OLS”), is readily available in over the counter econometric software. Another class of procedures, called generalized least squares (“GLS”), is appropriate under assumptions of more complicated error specifications. For example, GLS estimation procedures can permit the variance of the error terms of cost models to be heteroskedastic in the sense that they vary across companies. Variances can, for example, be larger for companies with large operating scale.

Estimation procedures that address *several* of the error term issues that are routinely encountered in utility benchmarking are not readily available in commercial econometric software packages such as Gauss and Stata. They require, instead, the development of customized estimation programs. While the cost of developing sophisticated estimation

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<sup>18</sup> We have elected not to log a few of the variables that assume a value of zero.

procedures that are tailored for benchmarking applications is sizable, the incremental cost of applying them to different utilities is typically small once they have been developed.

In order to achieve a more efficient estimator, we used a GLS estimation procedure that corrected for autocorrelation and heteroskedasticity in the error terms. These are common phenomena in statistical cost research. The estimation procedure was developed by PEG Research using the GAUSS statistical software program. Since we estimated these unknown disturbance matrices consistently, the estimators we eventually computed are equivalent to Maximum Likelihood Estimators (MLE).<sup>19</sup> Our estimates thus possess all the highly desirable properties of MLEs. Note also that cost and cost share equations were estimated simultaneously, and our regression procedure allows for correlation between the error terms of these equations.

Note, finally, that the model specification was determined using the data for all sampled companies, including PGE. However, computation of model parameters and standard errors for the prediction required that the utility of interest be dropped from the sample when we estimated the coefficients in the predicting equation. This implies that the estimates used in developing a model will vary slightly from those in the model used for benchmarking.

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<sup>19</sup> See Dhrymes (1971), Oberhofer and Kmenta (1974), Magnus (1978).

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