

An EDISON INTERNATIONAL<sup>SM</sup> Company

1994 Commercial CFL Manufacturers' Rebate Persistence Study ID 529D

March 1999

**Decision Sciences Research Associates, Inc.** 

236 West Mountain Street, Suite 103 • Pasadena, California 91103 Voice: (626) 793-9090 Fax: (626) 793-9051



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## **EXECUTIVE SUMMARY**

This research performs a measure retention study for Edison's 1994 Commercial CFL Manufacturer's Rebate Program. The evaluation estimates expected useful lives (EULs) for fixtures covered in the program and compares them to *ex ante* EUL estimates filed earlier. In addition bulb EULs are also estimated. A follow-up inspection sample was used to determine retention with inspectors looking for tags applied in the first-year evaluation. Statistical models were used to extrapolate the retention rates to the time when half the units will remain.

#### **KEY FINDINGS**

#### Fixtures

- Fixture EUL estimates are particularly sensitive to model specification and assumptions about the future pattern of survival. Too little time had passed at the inspection to make reliable estimates of EUL. Integral screw-in units, which have much shorter expected lives, are an exception to this and robust estimates could be developed.
- EULs were estimated using a variety of approaches and produced point estimates which range 4.3-9.4 years overall, with wide confidence intervals due both to the distant period tested in the extrapolated forecast and larger sampling errors due to cluster sampling.
- EULs for integral units are estimated at 2.7-3.1 years with 80% confidence intervals which would suggest *ex ante* estimates of 2.2 years are too conservative.
- With the great deal of uncertainty with predicting fixture EULs after only 2.7 years has elapsed from installation on average, there is no basis for rejecting the overall *ex ante* EUL estimate of 12.2 years for modular CFL fixtures or the program overall.

#### **Bulbs**

- Bulb EULs are estimated to be 2.8 years +/- .2 years.
- Forecasts are not particularly sensitive to model specification.
- Prior predictions of 2.2 years are conservative.



#### **INTRODUCTION**

#### **OBJECTIVES**

Measurement and evaluation protocols adopted by the California Public Utilities Commissions require utilities making earnings claims to substantiate these claims with measure retention studies. This study reports the results of a  $3^{rd}/4^{th}$  year retention study for SCE's 1994 Manufacturer's Rebate Commercial CFL Program. That program distributed over 320 thousand subsidized compact fluorescent fixtures and bulbs.

The objectives of this study are to:

- To estimate the extent to which these fixtures were still in place at the time of our second inspection
- To estimate the expected useful lives (EULs) of these fixtures and bulbs, and
- To compare EUL fixture estimates to *ex ante* EUL estimates at the 20% significance level (*80% confidence level*).

*Ex ante* estimates were filed at 12.2 years for fluorescent hardwire fixtures and modular screw-in units with replaceable lamps. *Ex ante* estimates were 2.2 years for integral, screw-in, disposable units, which have a fixture EUL tied to lamp life. This latter lamp type accounted for only 4.2 percent of program savings and 4% of bulbs.

#### DATA COLLECTION

A follow-up inspection sample was conducted from November 1996 through March 1997 to measure retention of program measures. The fixtures inspected were originally tagged as part of the research connected with the First-Year Program Evaluation research that was conducted in November 1995-January 1996. Inspectors had applied tags to lighting fixtures and bulbs and mapped where these tagged units were located among hundreds or thousands of other fixtures at the customer site, so that they could be relocated at the follow-up inspection. Fixture and bulb retention could be measured separately. Inspectors also tested the operation of the lamps, when possible (lighting on timers couldn't be checked for its operation).

Retention is defined as the fixture being located in the same place with the same unit tag. Inspectors made no attempt to determine whether fixtures removed due to remodeling were recycled for use at another part of the site as we think the possibility is not likely. It would also be hard to determine given the numerous maintenance and construction employees making such decisions. Operability is required in the retention definition, but



does not appear to be an important retention consideration. We found 100 percent of tested bulbs were operable, although only 56 percent of bulbs could be tested because the balance were controlled by photosensors or timers.

We are satisfied that this approach to measuring retention was successful because of our over 95% ability to locate and inspect units for this evaluation. This method is far superior to a telephone conversation with a site representative asking them to estimate what percent of hundreds of program bulbs among possibly thousands of all types of bulbs at the site had failed and when. We found that this approach was suitable for the large commercial sites that participated in this program.

With only 2.7 years passing on average from installation to the current inspection we are unsatisfied that enough time has elapsed to make precise estimates of fixture lives from the available data. Nor have we found alternative data sources that would be applicable to a commercial program of this type. Enough time has passed for estimating bulb life and for integral screw-in fixtures whose lives are tied to bulb life alone.



#### METHODOLOGY

#### **EVALUATION METHODS**

This research used:

- a follow-up sample to determine retention of fixtures and bulbs
- modeling to forecast EULs, and
- weighting and statistics for cluster samples

Follow-up on-site inspections were made in December 1996-March 1997 for a panel of bulbs and fixtures tagged as part of an earlier study of this program (Decision Sciences' SCE 1994 Commercial CFL Evaluation: First Year Impact Evaluation Report, Study ID # 561, February 1996). Tagged on-site inspections were selected as a superior methodology to mail or telephone follow-up surveys that would have to inquire about the status of hundreds of program bulbs and fixtures at these commercial customers' sites. During the first round of visits, Decision Sciences' inspectors tagged installed program product on both fixture and bulb as modular products can have bulbs replaced while the fixture (ballast) remains in service. These tags were applied during November 1995-January 1996 in anticipation of the follow-up inspections which were conducted on average 360 days later. By that time an average of 970 days (2.7 years) had passed since the installation of these bulbs and fixtures. Inspectors identified the fixtures from information prepared in the earlier inspection and recorded bulb and fixture status (e.g., present, removed, damaged, not present, different CFL bulb, etc) and tested operation if possible. Inspectors did not try to determine the date when specific fixtures were removed and or bulbs replaced. With an average of 300 total program bulbs per segment it would be unlikely that customers would remember consistently when specific units had been changed or that a knowledgeable customer contact could be found at all. Thus we know all fixtures were operating at the first-year inspection and some fraction were not operating or still present at the second inspection.

The sample of fixtures impaneled for follow-up inspection was the result of a multi-step sampling process used to identify installed program product. This program used manufacturers' rebates to achieve low administrative cost and a substantial market transformation. Program invoices tracked sales from manufacturers to distributors and TAG data forms tracked product to end-user purchases. Inspectors identified usage segments (*groups of fixtures in a common location with a common method of control*) at cooperative customer sites for follow-up evaluation in the first-year evaluation.

Table 1 summarizes data from the 203 customer locations that were visited during the first year's study. At 152 of these sites, inspectors found CFL program product in 210 identified usage segments. Note that the inspectors tagged fixtures in segments only where they were given permission to do so and had ease of access. In all, inspectors tagged 681 fixtures in 163 usage segments at 113 locations. These fixtures, segments and locations constituted the sample frame for the planned persistence follow-up inspections.

#### Table 1 – Initial Field Inspection Counts

	Customer Locations	Usage Segments	Tagged Fixtures
1st Field Inspections			
Dec 1995 - Jan 1996			
End-user sample locations inspected	203		
No product found	(51)		
CFL Program product found	152	210	
Persistence tags and marks applied	113	163	681

Table 1 presents the results of the Persistence Study follow-up visits.

#### Table 2 – Persistence Inspection Counts and Results

			Customer	Usage	Tagged
and Field Inspection			Locations	Segments	FIXIULES
Dec 1997 - Apr 199	8				
Increation Visit 6					
Inspection visit s	Status			(2)	<i></i>
Locations not	visited		(3)	(3)	(14)
Persistence lo	cations inspected		110	160	667
Fixture Inspectio	n Status				
	Could not locate or iden	ntify			(32)
	Could not Inspect				(5)
	Fixtures Inspected				630
Fixture Inspectio	n Results				
Out of Ser	vice				
	Removed, no replacement	ent lighting			(68)
	Damaged not working				(1)
	Empty (no bulb)				(2)
In Service					
	Total bulbs found in fixt	ures			559
		Originals			353
		CFL replace	ments (like-	for-like)	197
	-	Non-CFL re	placement		9



Table 2 shows that of the 113 persistence frame locations, three were unavailable for follow-up inspections. Decision Sciences' inspectors were able to visit 110 locations to determine the status of 667 fixtures. The results of these inspections are shown in the rightmost column of Table 2. Figure A-1 (see Appendix A) provides a dataflow diagram of the sample and inspection datasets that comprise the initial and follow-up observations for this study.

The resulting sample cannot be considered a probability sample. As such, installed bulb type distributions derived from the original Program Invoice Tracking file were used to weight this sample to make it more representative of the program population. Further, this sample is a cluster sample of fixtures with a common type and use (e.g., room lighting, exit signs, etc.) that were aggregated into usage segments at the customer site. Fixtures were not selected independently and cluster sampling formulas are applied in the calculation of sampling errors.

Several techniques were used to assess EULs for the modular and integral fixtures and bulbs, including survival analysis, linear and exponential (constant percent, continuously compounded decay) models. With only 2.7 years of time elapsed for modular models and only one follow-up, considerable uncertainty surrounds the estimates. EULs are quite sensitive to assumptions made about the shape of decay in retention. For integral units, 2.7 years was sufficient to test the *ex ante* estimate with its shorter expected 2.2 year life.

#### **MODELING METHODS**

Beyond the reporting of retention results for this inspection sample, this study goal is to estimate the half-life of the measures in the field, the elapsed time at which 50% of program units remain, which is the definition used for EUL. With only 2.7 years of time elapsing since installation, a forecast needs to be made well into the future for fixtures expected to live more than 12 years. Under these circumstances the forecast will be sensitive to the functional form of the estimating equation.

Traditionally, analysts would use survival techniques to extrapolate from observed measure failures to date using a hazard function fit to a selected cumulative density function and a procedure such as SAS's PROC LIFEREG. While we use that approach here, we use two alternatives too, because of the nature of this data. Too short a time period has elapsed and we couldn't determine the date of removal so the fixtures not retained are interval censored, having failed/been removed sometime between inspections. Retained fixtures are right censored with an unknown future date of failure. Some tested survival models didn't converge to a solution with this data. Further, we believe the

survival models are not the best choice for making future forecasts when so few failures have been observed.

These data might be conceptualized as simply three data points, sample estimates of the percent remaining at three time points. All fixtures were alive at installation and these inspection fixtures were also alive at the first inspection<sup>1</sup> which averaged 600 days or 1.7 years<sup>2</sup> later. At the second inspection some percentage of fixtures/bulbs failed and we don't know when. This second inspection was on average 360 days later. The inter-quartile range ( $25^{th}-75^{th}$  percentile) of the dates for the first inspection was only 13 days and the same range for the second inspection date was only 33 days, so during the period when deaths could occur we have little variation on dates. Installation date varied more with an interquartile range of 242 days. With so little variation in the data we have the choice of fitting models to the endpoints of the period or piecewise (i.e. Installation-Inspection 1 and then from Inspection 1 – Inspection 2). The objective is not to find the closest fit to the observed data we have, but rather to make the best forecast of program measure half-life which occurs beyond the range of our data. As we will see below the observed data don't provide enough variation to choose among the alternatives based on fit.

No single functional form is an obvious choice for this particular retention curve. The concave pattern of survival to the origin observed here is unusual except in cases where too little time has elapsed to observe the L-shaped pattern that is usually observed in measure life studies. The predominant cause of failure to retain fixtures in the commercial sector is architectural change, so patterns from engineering or other third-part studies are not likely to predict specific patterns for this study. As a result we have modeled several ways using endpoint or piecewise fits and linear, exponential, and selected survival analysis models showing how the result is dependent on the assumptions made.

<sup>&</sup>lt;sup>2</sup> Program product at customer sites from an earlier pilot program conducted in the Coachella Valley is included in this retention study, inspectors couldn't distinguish fixtures by year. As the same types of fixtures were covered this should not effect the retention analysis and may even increase the period of observation which is a benefit. Note that 30 percent of fixture installation dates weren't known about even distributed between Coachella Valley and other locations. We imputed missing installation dates using the median separately for Coachella Valley and Other due to the difference the pilot program made in determining date installed.



 $<sup>^1</sup>$  Recall that the First-Year Evaluation was quite conservative on counting installed measures. Only measures installed and still working at the first inspection were counted in estimating program savings.

The graphs on the next pages portray a picture of the modeling alternatives under these circumstances, with endpoint models, piecewise models and a survival curve. The first graph Figure 1, shows endpoint models for linear and exponential functional forms.



Figure 1 – Endpoint Models, Linear and Exponential Functional Forms

The vertical reference line at 2.7 years delimits the border between the observed and forecast periods. In the observed period the difference between a linear and exponential model is nearly undetectable. In the forecast period an exponential form diverges from the linear form, estimating longer EULs and shows a pattern more like that seen product in failure research. The linear function assumes the average absolute decline per year will proceed into the future. The exponential function assumes that the average, continuously compounded percent decline will continue into the future. We would need substantially more failures, 35% or more, to distinguish between these models.

In Figure 1, the point estimate of EUL would be found by finding the time value at which the survival curve intersects with a horizontal line at the 50% remaining level. You can easily see EUL will be much longer when the Exponential model is used. Our experience



suggests that survival curves stop their quick drop off after a time and the rate of decline slows forming an L-shaped pattern.



Figure 2 – Piecewise Models, Linear and Exponential Functional Forms

Figure 2 graphs linear and exponential models using a piecewise fit to the observed three data points. Again the difference between a linear and exponential model is nearly undetectable during the observed period but diverges as elapsed time increases. In this modeling alternative estimated EULs are shorter because the estimated slope between inspection periods is steeper. The assumption in this graph is that the rates of decline observed between the two inspections will continue into the future and that this is a better assumption than the alternative that the average rate of decline since installation (as illustrated by Figure 1) will continue. The question is whether it is better to forecast using average decline between endpoints over 2.7 years or to use the decline rate for nearly 1 year between inspections to forecast the future.

What is needed is another data point 6-8 years after installation, which would easily distinguish among these modeling alternatives. For the moment we can conduct sensitivity analyses and rely on our expertise to predict the future.



Figure 3 – Survival Models, Log Normal Distribution

Figure 3 shows that a survival model fit to the observed data using SAS<sup>™</sup> PROC LIFEREG and the log normal distribution is closer to a piecewise fit than the endpoint model. It is trying to fit the limited amount of observed data and is using the rate of decline observed between inspections. The survival model fits the cliff in the data and drops at a rate even more quickly than a piecewise linear model. A survival model allows for a change in the rate of change, a point of inflection. Linear models hold change constant and exponential models hold the percent change constant at a fixed level.

The best way to forecast into a distant and uncertain future is unclear. Each of these five types of modeling alternatives will make a good forecast only if the assumptions about the future rates of change embodied in the model hold. The exponential models are the ones

capable of allowing the L-shaped pattern to develop, which we believe would be observed, if enough time had elapsed. So, we favor them over the alternatives in this situation.

#### **Linear Models**

If we denote the three time points as  $t_1$ ,  $t_2$ , and  $t_3$  and the percent retained as  $y_1$ ,  $y_2$ , and  $y_3$  then the slope is determined by

Endpoint model:	Slope =	(y <sub>3</sub> - y <sub>1</sub> ) / (t <sub>3</sub> - t <sub>1</sub> )
Piecewise model:	Slope =	(y <sub>3</sub> - y <sub>2</sub> ) / (t <sub>3</sub> - t <sub>2</sub> )

with slope for the first piecewise segment of zero.

For example, if we have 80 percent retention after two years, the rate of decline estimated is 10 percent per year. If alternatively we use a piecewise fit and spread the decline over one year the rate of future decline is 20 percent per year or double that estimated by the endpoint model. Comparing the two linear models in Figure 1 and in Figure 2 shows the impact on forecast.

#### **Exponential Models**

Exponential models hold the percent change fixed, where the percent remaining is given by...

Percent Remaining =  $100 * \exp(g * dt)$ 

where

g = the constant proportion changedt = the change in time

If we denote the three time points as  $t_1$ ,  $t_2$ , and  $t_3$  and the percent retained as  $y_1$ ,  $y_2$ , and  $y_3$  then the percent change is determined by...

Endpoint model:	Percent Change =	100 * ln (1+y <sub>3</sub> - y <sub>1</sub> ) / (t <sub>3</sub> - t <sub>1</sub> )
Piecewise model:	Percent Change =	100 * ln (1+y <sub>3 -</sub> y <sub>2</sub> ) / (t <sub>3 -</sub> t <sub>2</sub> )

with change for the first piecewise segment of zero.

For example, if we have 80 percent retention after 2 years, the percent rate of decline estimated is 9 percent. If alternatively we use a piecewise fit and spread the decline over one year the rate of future decline is 18 percent or double that estimated by the endpoint model. Comparing the two exponential models in Figure 1 and in Figure 2 shows the impact of assumptions on forecast.



#### **Survival Models**

Survival modeling first fits a hazard function (the probability the unit will fail in time period t, given that it has survived to that time) to the data. The cumulative percent failing is fit to the parameters of a selected cumulative density function as a function of time t and sometimes other parameters (*see SAS/STAT User Guide, Volume 2 for more details*). Survival at time t has the probability of 100 - the accumulated hazard to that point.

The use of a model probability density function allows survival analysis to make predictions beyond the scope of the data. These distribution functions can change the rate of decline and in the change of the change in the rate of decline (2<sup>nd</sup> derivative) allowing for an inflection point and is more flexible than the prior two model types. Some probability distributions allow for declining, constant and even accelerating rates of failure. Below we report results for the Log Normal, Logistic, and Weibull distributions to demonstrate that this variety of alternatives all estimate similar EULs based on these data. However, when we view Figure 3, we see that fitting a survival model to a short segment of a survival period can cause the estimated function to twist downward in the forecast period to estimate a rate of decline faster than even a piecewise linear model. We have likened this tendency to its assuming a piecewise fit, because its trying to fit the limited data observed to date rather than make the best forecast of the future retention experience.

Hints that survival models may not be appropriate come from evidence that the tests with the gamma distribution don't converge. No survival analysis converged for integral screwin fixtures for any tested distribution with a sample size of 79. Note too that all failures were interval censored and that all remaining data were right censored. The biggest drawback of using the survival models is having no data point far enough in to the future to have the functions bend to fit the declining rate of decline that we predict will occur.

While it is possible to introduce covariates into the survival model, we have chosen to use none, although we report results separately by fixture type and for a weighted distribution of fixtures and bulbs. We do this because the objective of this study is to estimate a median, the EUL. We want to use the predicted quantiles (50<sup>th</sup> percentile in particular) and their standard errors to predict EUL. Using covariates would complicate the prediction procedure without providing precision benefits.

#### **Cluster Sample Variances**

The inspection sample is a cluster sample. Several fixtures (*an average of 4.1 per segment*) were selected from among all the program measures in the segment (*on average, 300 per segment*). More bulbs were selected when more measures were in the segment. As the fixtures were not selected independently, the common simple random sample formulas for sample variance don't apply. If architectural renovation occurs all the fixtures in a segment may be replaced producing an estimate that is noisier than a simple random sample and one that may be biased in the case of unequal clusters such as this sample.

The estimation formulas below for calculating upper and lower boundaries of the 80% confidence interval as required by evaluation protocols take into account this sample structure. The variance of the ratio estimate of percent retained is

Variance  $r = 1/x^2 [(\Sigma (y_a + y^2 / a) + r^2 (\Sigma (x_a + x^2 / a) - 2 r (\Sigma (y_a + x_a - yx / a))])]$ 

where...

a = index of the segment and count of number of segments

 $x = \Sigma x_a$  the sum of all units tracked on all a segments

 $y = \Sigma y_a$  the sum of all retained units tracked on all a segments

r = the ratio estimate of percent units retained = y/x

 $x_a$ = the sum of all units tracked on this segment

 $y_{a=}$  the sum of all retained units tracked on this segment

This formula was used below in the calculations for sampling error.

#### Modular vs. Integral

Modular CFL units predominated the measures distributed under this rebate program. Some integral units were also included in the program. Integral units fail when the bulb fails regardless of whether the ballast was still working. So, EUL estimates for integral units were estimated to be only 2.2 years versus 12.2 years for modular fixtures. As our sample is not a probability sample we need to control for this different type of unit which accounted for about 4 percent of program units and savings. We control for these differences by weighting the data to be representative of the installed population.

The only integral units found in the retention sample were the Feit 18 watt, integral unit, model ESL18. This is not surprising as this model accounted for eleven thousand of the thirteen thousand integral units in the program (85 percent). These units will be treated separately in the weighting discussed below.



#### **ANALYTICAL RESULTS**

#### **DESCRIPTIVE STATISTICS**

The follow-up sample included 113 customer sites with 163 lighting segments and 681 fixtures. The inspectors were successful in performing follow-up evaluations over 95 percent of the time. Among the units not evaluable, reasons were about equally split between not being able to visit site and not being able to identify or inspect units at a visited site as shown in Table 3.

		Fixtures		В	ulbs
Inspection Result		Count	Percent	Count	Percent
	Site Not Visited	14	2.1%	14	2.1%
	Visited: Not Evaluable	15	2.2%	13	1.9%
	Visited: Evaluable	652	95.7%	654	96.0%
	Total	681	100.0%	681	100.0%

#### Table 3 – Percent Evaluable

Note: Not Evaluable for fixtures includes unable to inspect or identify and empty fixtures; for bulbs it includes unable to inspect or identify.

Table 4 shows that among the evaluable units 79 percent of fixtures and 54 percent of bulbs were retained. Fixtures were primarily not retained due to removals, often as the result of remodeling. Integral fixture failures, whose unit life is linked to bulb life, accounted for most of the rest of fixture failures.

	Fixtures		Bulb	)S
tention Status	Count	Percent Count Pe		Percent
Retained	516	79.1%	353	54.0%
Not Retained				
Different CFL bulb			163	24.9%
Different Integral unit	34	5.2%	34	5.2%
Not present/removed	92	14.1%	92	14.1%
Damaged	1	0.2%	1	0.2%
Empty no CFL			2	0.3%
Replaced with incandescent	9	1.4%	9	1.4%
Not Retained Subtotal	136	21%	301	
Total	652	100.0%	654	100.0%

#### Table 4 – Distribution of Evaluated Fixtures and Bulbs



Reasons for bulb failures were different. Changes in modular bulbs and integral unit bulb replacements were collectively twice as important as unit removals in accounting for total original bulb removals. Note that these are unweighted percentages and just report the raw distribution in our sample.

#### WEIGHTING

The sample of fixtures identified is not a probability sample of the units installed under the program. Considerable effort was necessary to track manufacturers rebated product to its final installation. Moreover, it is not cost effective to take a random sample of all fixtures when on-site inspections must be performed. This original sample selected for the First-Year Evaluation was a cluster sample of fixtures on common lighting segments with like lighting units. Inspectors could visit a smaller number of sites and identify cluster of fixtures throughout the site. Operational considerations were important too, segments average thee hundred fixtures each and some sites had up to sixteen thousand program fixtures. There were many large commercial sites, particularly in the hospitality segment. Not all fixtures in a segment were sampled for follow-up evaluation, but keeping the tagged fixtures clustered together improved the chances that units could be found again on the second inspection visit. Our rate of evaluability was 95% on re-inspection.

Table 5 shows that 55 percent of sampled segments had only 1-2 fixtures tagged, 22 percent had 3-5 fixtures tagged and 16 percent had 6-10 fixtures tagged on the segment. Only a few segments had a large number of fixtures tagged. The mean was 4.1 fixtures inspected per segment versus an average of 311 and median of 30 program fixtures per segment.

Number of Tagged	Percent
Bulbs per Segment	Distribution
1	38.0
2	17.1
3 - 5	21.5
6 - 10	15.8
11 - 15	3.8
16-20	2.5
21 +	1.3
Total	100.0

#### Table 5 – Frequency of Segments by Number of Inspected Fixtures Category

Variance estimation takes the lack of independence between bulb and fixture retention into account when computing confidence intervals.

The tracking system for manufacturer rebates accounted for units by wattage class category. This system's totals were used in the First-Year Evaluation to produce estimates by wattage class. The estimates from that report for units installed were used to weight the fixtures in the current follow-up sample to make them more representative of the program population. Table 6 shows the percent distribution of the population and the follow-up sample by watt class and integral/modular unit type. The rightmost column reports the resulting weight.

Watt Class	Туре	Population	Count	Sample	Weight
4-13	Modular	56.4	374	57.4	0.9834
14-20	Modular	10.3	66	10.1	1.0175
14-20	Modular	4.0	79	12.1	0.3301
21+	Modular	23.9	133	20.4	1.4364
All Classes	Modular	100.0	652	100.0	1.0000

#### Table 6 – Weight Calculation

Note that the estimate of integral units comes from a separate tabulation on the tracking system and that the small 45+ watt category in the First-Year Evaluation, Table 3 has been combined with the 21+ watt class for lack of sample in the inspection data.

Feit 18 watt, integral units model ESL18 accounted for eleven thousand of the thirteen thousand integral units subsidized by the program. They are the only integral units found in the inspection sample. The integral units are over represented in the sample given their percent distribution in the population and are given a weight of .33. Given their lower expected life it is important to represent their proportion properly. This overrepresentation may have derived from a pilot project in the Coachella Valley emphasizing such units, an area where we were able to track program product more readily. Conversely, 21+ watt units are underrepresented and have been weighted to compensate for this.

#### **EUL ESTIMATES**

#### FIXTURES

Fixture lives were estimated using the linear, exponential and survival analysis models discussed in the methodology section above, solving for the median life. Upper and lower bounds were calculated using the sampling error reported from the parameter estimate or the prediction error reported from the survival model. Figure 4 shows how the point estimates and upper and lower confidence bounds are determined for the simple exponential endpoint model. That model is based on a single parameter, the percent remaining at the second inspection.





We estimated the point estimate and the bounds of the 80 percent confidence interval for percent remaining which are defined as +/- 1.28 standard errors based on the cluster sample formula described above. We then solved for the rates of decline for each value (- 5.1%, -7.9%, and -10.8% for the upper bound, point estimate, and lower bound respectively). Figure 4 plots these rates of decline. The EULs reported are the times at which the estimated percent remaining equals 50% for each curve.

Survival model output from SAS<sup>™</sup> PROC LIFEREG provides estimates for quantiles and their standard errors. Sampling errors are up to three times larger for this cluster sample than for a simple random sample of like size. As survival models don't take into account clustering, reported confidence bounds for survival models are based on the reported standard error at the 50<sup>th</sup> percentile multiplied by 1.28 multiplied by the estimated design effect (deff) for the cluster sampling.

Estimates are made for Modular Units, Integral Units and All Unit Types weighted to be representative of the program fixture population. Table 7, on page 19, shows a wide range of estimates as expected depending on unit type and statistical model.

The endpoint models predict longer lives than the piecewise models. For example, for modular fixtures the linear endpoint model predicts an EUL between 5.5 and 11.7 years, while the piecewise linear model predicts 3.7 - 6.0 years and the survival models predict even lower EULs. Note that the 'dc' entry for the integral unit survival models means the model didn't converge. The forecasts vary markedly depending on analyst's choice of what model predicts the future best, as too little time has elapsed to choose among these shapes with the observed data. We believe the endpoint, exponential model is the most likely to approximate the future based or product hazard shapes observed elsewhere. It is possible, however, that architectural renovations in the commercial sector have hastened the removal of program product at a rate faster than that due to physical degradation. The survival models estimate similar EULs regardless of distribution (Log-Normal, Logistic, or Weibull) used. We doubt that the survival models provide good EUL forecasts given the limited data and the convergence problems experienced in searching for solutions may signal the instability of their results.

With more integral units failing (43%) during the study period, we can be more definite in our conclusions. EUL estimates lower bounds for integral units exceed the *ex ante* estimate of 2.2 years with point estimates of 2.7 - 3.1 years. Neither interval censored nor assumed midpoint survival models converged for this small sample of integral units, so the alternative models are used to make EUL forecasts. The *ex ante* estimate was conservative.



	Endpoint Models		Piece	wise Mod	dels	
	Lower		Upper	Lower		Upper
Model Type	Bound	Mean	Bound	Bound	Mean	Bound
Modular Fixtures						
Linear	5.5	7.5	11.7	3.7	4.4	6.0
Exponential	6.6	9.4	15.3	4.1	5.2	7.3
Survival Curve						
Logistic				3.1	3.4	3.6
Log Normal				3.2	3.6	4.1
Weibull				3.1	3.4	3.8
Integral Fixtures						
Linear	2.5	2.9	3.6	2.5	2.7	2.9
Exponential	2.5	3.1	4.0	2.5	2.7	3.1
Survival Curve						
Logistic				dc	dc	dc
Log Normal				dc	dc	dc
Weibull				dc	dc	dc
All Fixtures						
Linear	5.3	7.1	10.5	3.6	4.3	5.6
Exponential	6.4	8.8	13.6	4.0	4.9	6.7
Survival Curve						
Logistic				3.1	3.4	3.6
Log Normal				3.2	3.6	4.1
Weibull				3.1	3.4	3.8

#### Table 7 – Predicted Fixture EUL (Years)

For all units combined, the EUL estimates are essentially similar to those for the modular bulbs that represent 96 percent of the total. Estimates range widely and the model we believe is lowest risk in forecast includes the *ex ante* estimate in its confidence interval. There is not sufficient evidence to reject the null hypothesis that they are the same at the 80 percent confidence level. More follow-up research would be necessary to make a tighter forecast. This retention question begs for more data over a longer time period.

The cluster mean where cluster sizes vary is a ratio estimate. This mean can be biased due to the lack of independence among observations. The overall weighted retention ratio estimate after 2.7 years was 81.1 percent. The mean of among the segments, which are nearly independent (there are only 1.3 lighting segment clusters per customer) was 81.2 percent and the segment means weighted by bulb type was also 81.1 percent. With so little variation among these methods of calculating the percent retained ,we conclude that the

bias is of little concern. Our analysis does, however, recognize that cluster sampling entails higher estimate variances.

One other type of sensitivity analysis was performed to test the sensitivity of results to outlying observations. One customer site, a golf course, had 16,000 program units installed (5% of the program total). Due to remodeling a golf course green, 47 percent of the 34 fixtures tracked were removed. This is a consequence of having our segment tags in too concentrated a space. We know that 47 percent of this site's bulbs weren't actually removed. Dropping this one site from our analysis to test sensitivity raised overall retention rate at 2.7 years from 81.1 percent to 82.7 percent. This change would raise expected EUL by 8 -10 percent, so our results are sensitive to the lack of independence among sampling elements. True retention rates may be somewhat higher than estimated in Table 7.

#### **BULBS**

Bulb lives were likewise estimated using the linear, exponential and survival analysis models. Upper and lower bounds were calculated using the sampling error reported from the parameter estimate or the prediction error reported from the survival model. The overall weighted retention after 2.7 years was 53.7 percent. Combined results are reported because bulb lives are estimated to be the same for different unit types.

Table 8 shows that all estimation techniques produce point estimates within .3 years of one another. Endpoint models produce estimates .1 - .2 years (up to 7 percent) higher than the piecewise models.

		Endpoint Models			Piecewise Models			
		Lower	Mean	Upper	-	Lower	Mean	Upper
Model Type		Bound		Bound		Bound		Bound
All Bulbs								
Linear	r	2.6	2.9	3.2		2.6	2.7	2.9
Expor	nential	2.5	3	3.5		2.6	2.8	3
Surviv	/al Curve							
Lo	ogistic					2.7	2.8	2.9
Lo	og Normal					2.7	2.8	2.9
W	'eibull					2.7	2.8	2.9

#### Table 8 – Predicted Bulb EUL (Years)

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Survival models produce estimates similar to the piecewise fit models which is why they are grouped under that category. The results are not particularly sensitive to model specification, when the forecast need only be extrapolated from 53.6 percent remaining to estimate the time at which only 50 percent will remain. Earlier estimate that bulbs would last only 2.2 years are conservative.

The appendix provides some additional retention percentages by watt class of the bulbs and whether the bulbs were used in indoor or outdoor applications. These statistics are not needed for EUL estimation, but may be of more general interest to researchers studying the durability of these measures in the commercial sector.

## **APPENDIX A - M & E Protocols Required Tables**

TABLE 6 -	<ul> <li>Results Used to Support PY94 Second</li> </ul>	l Earnings Claims

	-			
<b>1. Measure:</b> Commercial CFL lighting fixtures installed u	under SCE's 1994 Manufacturer's			
Rebate Program from various manufacturers and wattages	s for the end-use lighting.			
<b>2. Ex Ante:</b> The <i>ex ante</i> EUL, expected useful life for thes	e measures:			
Modular screw-in and hardwire fixtures	12.2 years			
Integral screw-in fixtures	2.2 years			
Combined	11.8 years			
Note: combined estimate is weighted mean of two measure	e types with weights of 95.8% and			
4.2% respectively. Stated program EUL filed by SCE was 1	12.0 years. <i>Ex ante</i> estimates of			
12.2 for modulars and 2.2 for integrals are listed in CPUC	Protocol Table F based on the			
CADMAC measure life study.				
<b>3. Ex Post:</b> The <i>ex post</i> EUL, expected useful life for these	measures:			
Modular screw-in and hardwire fixtures	9.4 years			
INTEGRAL SCREW-IN FIXTURES	3.1 YEARS			
Combined	8.8 years			
Based on the endpoint exponential model, which is expected	ed to best predict the future			
survival curve.				
4. Ex Post EULs to be Used in Earnings Claims: The	ex post EUL to be used in future			
earnings claims for these measures:				
Modular screw-in and hardwire fixtures	12.2 years			
Integral screw-in fixtures	3.1 years			
Combined	12.0 years			
Modular and combined av post FUL estimates are not diffe	prent from av ante estimates at			

Modular and combined *ex post* EUL estimates are not different from *ex ante* estimates at the 80% confidence level. Integral unit EUL estimates are higher but the combined EUL is to be used in future earnings claims and that remains at 12.0 years.

**5. Standard Errors: :** The standard errors for these models are based on the parameter estimate of the percent remaining at the time of the second inspection. This is expressed in terms of the percent remaining. The standard error are:

Modular screw-in and hardwire fixtures	5.1%
Integral screw-in fixtures	6.1%
Combined	4.8%

These standard errors are plugged into survival functions for the appropriate confidence interval to determine the point at which 50% would be remaining.

**6. 80% Confidence Interval:** The *ex post* EUL, expected useful life for these measures was:

Modular screw-in and hardwire fixtures	6.6 – 15.3 years
Integral screw-in fixtures	2.5 – 4.0 years
Combined	6.4 – 13.6 years

**7. P-value** – for the combined program *ex post* estimate of 8.8 compared to the filed *ex ante* estimate of 12.0 years the p-value equals .33 for the two-tailed or would require a 67% confidence interval.

**8. Realization Rate**: Realization rate for the combined program estimate which will be used in future earnings claims is equal to 1.0 as the *ex ante* estimate of EUL will continue to be used.

9. Like Measures: not applicable



# TABLE 7 - Documentation of Protocols For Data Quality and ProcessingA. OVERVIEW INFORMATION

**1. Study Title and Study ID:** Southern California Edison 1994 Commercial CFL Manufacturers Rebate Program Retention Study ID 529 D

**2. Program, Program Year or Years, and Program Description:** The 1994 Manufacturers Commercial Compact Fluorescent Lamp Program provided financial incentives directly to CFL Manufacturers to sell compact fluorescent equipment in Southern California Edison territory at discounted prices. In all, approximately 320,000 units were distributed under this program.

**3. End-Uses and/or Measures Covered:** Compact fluorescent fixtures, lamp assemblies, and bulbs used in commercial environments.

**4. Method(s) and Model(s) Used:** The methodology employed in this report consists of the estimation of EULs (effective useful life) of program product using alternative survival estimation strategies.

**5. Program Participants:** Program participants included manufacturers, primary and secondary distributors, as well as product end-users who purchased discounted CFL equipment within Edison territory.

**6. Analysis of Sample Size:** The sample used for this persistence study was the population of 113 customer locations which consisted of 163 lighting segments and 681 fixtures previously identified (*during the first year impacts evaluation*) for follow-up persistence inspections.

#### **B. DATABASE MANAGEMENT**

**1. Flow Chart Illustrating Relationships between Data Elements:** See Figure A-1, PY 1994 Commercial CFL Lighting Program Persistence Estimation

**2. Specific Data Sources:** Edison program tracking records, telephone books, and commercial sources were originally used to develop a frame of program participants including company names, addresses, and telephone numbers. Additional end-user customers identified by distributor survey respondents. Persistence study data included records collected as part of the first year impacts study and data collected during reinspection follow-up visits.

**3. Data Attrition Process:** Of the 113 sites identified for follow-up during the first year impact evaluation, 3 sites were not visited for various reasons including business closure, denial of permission and administrative convenience. A total of 3 lighting segments and 14 fixtures were lost to follow-up at these sites.

**4. Internal/Organizational Data Quality Checks and Procedures:** Data entry operations were subject to visual review and double-punch verification for key identifying variables and quantities. Follow-up data was keyed into spreadsheets from the transcribed inspection records.

5. Summary of the Data Collected but Not Used: None.





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#### **C. SAMPLING**

**1. Sampling Procedures and Protocols:** Persistence inspections were attempted at all customer sites where initial inspections occurred and program product was found and marked for follow-up.

2. Survey Information: No new surveys were conducted for this persistence study.

3. Statistical Descriptions: Not applicable.

D. DATA SCREENING AND ANALYSIS

**1. Procedures Used for Treatment of Outliers, Missing Data Points, and Weather Adjustment:** Not applicable.

2. Controlling for the Effects of Background Variables: Not applicable.

3. Procedures Used to Screen Data: Not applicable.

4. Regression Statistics: Not applicable.

**5. Specification:** Not applicable.

**6. Error in Measuring Variables:** Not applicable

**7. Autocorrelation:** Not applicable.

8. Heteroskedasticity: Not applicable.

**9. Collinearity:** Not applicable.

10. Influential Data Points: Not applicable.

**11. Missing Data:** Follow-up data was obtained during follow-up inspections for 96% of fixtures tracked. Missing data resulted primarily from customer refusals for re-inspection and inability to track a few of the tagged fixtures at visited customer sites. Missing data should be similar to the included data and combined with this low incidence of missing, non-response bias should be minimal. The tracked fixture data was also weighted by bulb class proportions estimated from the original rebate tracking system to reflect program totals correctly.

**12. Precision:** With only two data points the endpoint and piecewise models fit any linear or curvilinear model that includes these points perfectly. The forecast uncertainty derives from estimates of the percent remaining estimated from the inspection data. Confidence limits for that measure were derived using appropriate variance estimates for a cluster sample of lighting segments at customer's sites. For survival models precision was estimated from the standard errors reported from the SAS<sup>™</sup> PROC LIFEREG models; the width of the confidence interval (80%) selected by CADMAC; and an adjustment for the design effect from using a cluster sample where observations are not distributed independently of one another.

#### **APPENDIX B**

#### SUPPLEMENTARY TABULATIONS ON BULB RETENTION

This appendix reports some additional tabulations on retention of bulbs by bulb wattage and fixture type and by location of the lighting application. Table 9 reports the mean bulbs retained at 2.7 years as of the time of the second inspection. The table shows that bulbs in outdoor locations, in the 4-14 watt class were retained only 44 percent of the time compared to 53.7 percent retained overall. These bulbs were usually used along walkways and obviously were more susceptible to damage.

Watt Class	Туре	Inside	Outside	All
4-13	modular	73.4%	44.4%	51.1%
14-20	modular	69.4%	70.6%	69.7%
14-20	integral	55.6%	57.7%	56.9%
21+	modular	53.0%	51.5%	52.6%
Total		62.2%	47.3%	53.7%

# Table 9 – Weighted Percent of Bulbs Remaining at 2.7 Yearsby Bulb and Fixture Type and Location

For other watt classes differences between indoor and outdoor retention were not so pronounced. Integral screw-in and modular units over 21 watts which were used in room applications most often were also retained at a lower rate than the 14-20 watt modular units.

Table 5 of the First Year Evaluation Report showed that 77 percent of 4-13 watt bulbs were located in outdoor applications. Over 80 percent of remaining bulb classes were located in indoor applications. We note that weighting by bulb watt class essentially controls for indoor/outdoor distribution of bulbs and fixtures in the program population due to this relationship.

Hours of operation may have had some impact on retention. Outside bulbs averaged 4,581 hours of operation annually according to Table 5 of the First Year Evaluation Report, which was 40% higher than expected hours of operation. However, 21+ watt bulbs were used only 1,675 hours per year or 50 percent less than expected, but they still showed lower rates of retention.

#### **APPENDIX C**

#### DESCRIPTION OF PROGRAMS, SPREADSHEETS, OUTPUT AND DATA FILES

#### SAS Programs

ANALY01. SAS	Preliminary Crosstabs on Inspection 2 File - MPANALY		
BULBCLS2. SAS	Crosstabs for Weight Calculation		
CLUSTFRQ. SAS	Frequency by Cluster Size - Tracked Fixtures, Table 3		
CLUSTIM2. SAS Weighted Means Fixture Retention, Time Intervals, Total and by			
	Cluster		
CLUSTMN3. SAS	Sensitivity Test Wgtd. Means Approximate Cluster Size Weighting		
CLUSTMN4. SAS	Weighted Means Bulb Retention, Time Intervals, Total and by Cluster,		
	Bulb Survival Curves		
CUST312. SAS	312		
CUSTMICH. SAS	Validation Crosstab - Model Number by manufacturer and wattage		
GRAPHC. SAS	Produces Figures 1, 2, and 4, Survival Curves (CGM Output)		
MANUF. SAS	Crosstab to Look For Integral Screw-in Manufacturers and Wattages		
PERSI STA. SAS	Survival Estimates - Fixtures		
RAWFREQ. SAS	Crosstabs of Fixture and Bulb Status - Tables 1 and 2		
VALUES. SAS	Formats for MPANALY File Variables		

#### SAS Data Files

CFLTAG. SD2 TAG Form from Customer Invoices - Model Numbers at Sit	
	Invoices Found
MPANALY. SD2	Inspection 2 Analysis File - Bulb and Fixture Status
MRG_98. SD2	Preliminary Merge File
SEG_CFL. SD2	Segment Information Record
SEGMIFRM SD2	Counts of Total Bulb Types by Wattages for Segment
SI TEFRM SD2	Site Info - Source of City and ZIP Code Info

#### Spreadsheets

CLUSTMN2. XLS	Calculation of Cluster variances and DEFF- Fixture Retention
CLUSTMN4. XLS	Calculation of Cluster variances and DEFF- Bulb Retention
EULCFL2. XLS	Endpoint, Piecewise, Survival Curve Equations - Fixtures
EULCFL3. XLS	Only
RAWFREQ. XLS	Crosstabs of Fixture and Bulb Status - Tables 1 and 2
WEI GHTS. XLS	Weight Calculation

Progr	am Output		
	BULBCLS2. LST Output: Crosstabs for Weight Calculation		
	CLUSTMN2. LST	Output: Weighted Means Fixture Retention, Time Intervals, Total and	
	by Cluster		
	CLUSTMN3. LST	Weighting	
	CLUSTMN4. LST Cluster, Bulb Survival Curves		
	PERSI STA. LST Output: Survival Estimates - Fixtures		
	CUST312. LST 312		
	RAWFREQ. LST	Tables 1 and 2	

#### **APPENDIX D**

#### FIXTURE SURVIVAL FUNCTION MODEL OUTPUT

#### **Output from SAS PROC LIFEREG**

- 1. Modular Fixtures Weibull Distribution
- 2. Integral Screw-in Fixtures Weibull Distribution
- 3. All Fixtures Weibull Distribution
- 4. Modular Fixtures Log-normal Distribution
- 5. Integral Screw-in Fixtures Log-normal Distribution
- 6. All Fixtures Log-normal Distribution
- 7. Modular Fixtures Logistic Distribution
- 8. Integral Screw-in Fixtures Interval Censored Logistic Distribution
- 9. Integral Screw-in Fixtures Midpoint Estimate of Failure– Logistic Distribution
- 10. All Fixtures Logistic Distribution
- Notes: All models were weighted. Models did not converge when predictions and std are not reported in the lower panel. Integral models were interval censored for failures, except for one test using a midpoint time for failures to test whether these models would converge using such a model they didn't converge in any attempt.

Modular Fixtures - Weibull

Lifereg Procedure Data Set =WORK. CFLMRG Dependent Variable=Log(LOWER) Dependent Variable=Log(UPPER) Weight Variable =WEI GHT Noncensored Values= 0 Right Censored Values= 475 Left Censored Values= 0 Interval Censored Values= 99 Log Likelihood for WEIBULL - 308. 3754702 Variable DF Estimate Std Err ChiSquare Pr>Chi Label/Value **INTERCPT** 1 7.19910763 0.027688 67601.94 0.0001 Intercept SCALE 1 0.17231092 0.015897 Extreme value scale parameter **OBS** PROB SCREWI N PREDTI ME STD 1 0.25 0 1079.69 17.7737 2 0.50 0 1256.33 29.1781 3 0.75 0 1415.72 45.3560 Integral Fixtures - Weibull Lifereg Procedure Data Set =WORK. CFLMRG Dependent Variable=Log(LOWER) Dependent Variable=Log(UPPER) Noncensored Values= 0 Right Censored Values= 45 Left Censored Values= 0 Interval Censored Values= 34 Log Likelihood for WEIBULL - 73. 03486506 Variable DF Estimate Std Err ChiSquare Pr>Chi Label/Value **INTERCPT** 1 7.05648717 0.058066 14768.43 0.0001 Intercept 1 0.29424171 0.048371 SCALE Extreme value scale parameter

All Fixtures - Weibull Lifereg Procedure

Data Set =WORK. CFLMRG Dependent Variable=Log(LOWER) Dependent Variable=Log(UPPER) Weight Variable =WEI GHT Noncensored Values= 0 Right Censored Values= 520 Left Censored Values= 0 Interval Censored Values= 133 Log Likelihood for WEIBULL - 339. 3241618 Variable DF Estimate Std Err ChiSquare Pr>Chi Label/Value 1 7.20488004 0.027938 66504.78 0.0001 Intercept **INTERCPT** SCALE 0.184656 0.016296 1 Extreme value scale parameter **OBS** \_PROB\_ PREDTI ME STD 0.25 4 1069.36 17.9143 0.50 5 1257.90 29.4440

1429.66

46.2825

0.75

6

Modular Fixtures - Log Normal

Lifereg Procedure

Data Set=WORK. CFLMRGDependent Variable=Log(LOWER)Dependent Variable=Log(UPPER)Weight Variable=WEIGHTNoncensored Values=0Right Censored Values=475Left Censored Values=0Interval Censored Values=99

Log Likelihood for LNORMAL - 305.8060058

Variable DF Estimate Std Err ChiSquare Pr>Chi Label/Value 1 7.18876243 0.032314 49491.65 0.0001 Intercept **INTERCPT** SCALE 1 0.30694212 0.027391 Normal scale parameter **OBS** PROB SCREWI N PREDTI ME STD 1 0.25 1076.78 21.5630 0 2 0.50 42.7984 0 1324.46 0.75 0 79.3092 3 1629.11

Integral Fixtures - Log Normal Lifereg Procedure

Data Set =WORK. CFLMRG Dependent Variable=Log(LOWER) Dependent Variable=Log(UPPER) Noncensored Values= 0 Right Censored Values= 45 Left Censored Values= 0 Interval Censored Values= 34 Log Likelihood for LNORMAL -71.82058938 Variable DF Estimate Std Err ChiSquare Pr>Chi Label/Value **INTERCPT** 1 6.94759733 0.06494 11445.77 0.0001 Intercept 1 0. 42615165 0. 06449 SCALE Normal scale parameter

All Fixtures - Log Normal

Lifereg Procedure

Data Set=WORK. CFLMRGDependent Variable=Log(LOWER)Dependent Variable=Log(UPPER)Weight Variable=WEIGHTNoncensored Values=0Right Censored Values=520Left Censored Values=0Interval Censored Values=133

Log Likelihood for LNORMAL - 337. 3310726

Variable DF Estimate Std Err ChiSquare Pr>Chi Label/Value

 INTERCPT
 1
 7. 19530167
 0. 032643
 48587. 35
 0. 0001
 Intercept

 SCALE
 1
 0. 33073767
 0. 027822
 Normal scale parameter

OBS	_PROB_	PREDTI ME	STD
4	0. 25	1066. 59	21. 8441
5	0.50	1333. 15	43. 5178
6	0.75	1666. 33	81. 9044

Modular Fixtures - Logistic Lifereg Procedure

Data Set =WORK. CFLMRG Dependent Variable=LOWER Dependent Variable=UPPER Weight Variable =WEI GHT Noncensored Values= **Right Censored Values=** 475 0 Left Censored Values= Interval Censored Values= 99 0 Log Likelihood for LOGISTIC - 310. 8832051 Variable DF Estimate Std Err ChiSquare Pr>Chi Label/Value **INTERCPT** 1 1234. 26142 23. 55043 2746. 733 0. 0001 Intercept 1 144. 196502 12. 63205 SCALE Logistic scale parameter **OBS** \_PROB\_ **SCREWI**N PREDTI ME STD 1 0.25 0 1075.85 16.0811 2 0.50 0 1234.26 23.5504 3 0.75 0 1392.68 35.1543 Integral Fixtures - Logistic Interval Censor Lifereg Procedure Data Set =WORK. CFLMRG Dependent Variable=LOWER Dependent Variable=UPPER Noncensored Values= 0 **Right Censored Values=** 45 Left Censored Values= 0 Interval Censored Values= 34 Log Likelihood for LOGISTIC -74.49616669 Variable DF Estimate Std Err ChiSquare Pr>Chi Label/Value **INTERCPT** 1 1026. 16631 46. 98798 476. 9381 0. 0001 Intercept SCALE 1 190.88385 29.21534 Logistic scale parameter



Integral Fixtures - Logistic Midpoint

Lifereg Procedure

Data Set =WORK. CFLMRG Dependent Variable=ELP\_TIME Censoring Variable=CENSOR Censoring Value(s) = (x + y) = (x + y) = (x + y)1 Noncensored Values= 34 **Right Censored Values=** 45 Left Censored Values= 0 Interval Censored Values= 0 Log Likelihood for LOGISTIC -274.2515988 Variable DF Estimate Std Err ChiSquare Pr>Chi Label/Value **INTERCPT** 1 1010. 94234 48. 47757 434. 8817 0. 0001 Intercept 1 198.680229 28.72609 SCALE Logistic scale parameter

All Fixtures - Logistic

Lifereg Procedure

Data Set =WORK. CFLMRG Dependent Variable=LOWER Dependent Variable=UPPER Weight Variable =WEIGHT Noncensored Values= 0 Right Censored Values= 520 Left Censored Values= 0 Interval Censored Values= 133 Log Likelihood for LOGISTIC - 342. 0277874

Variable DF Estimate Std Err ChiSquare Pr>Chi Label/Value

INTERCPT 1 1232.80504 23.32502 2793.476 0.0001 Intercept SCALE 1 151.748823 12.676 Logistic scale parameter OBS PROB PREDTIME STD

0.25	1066. 09	16. 0866
0.50	1232.81	23. 3250
0.75	1399. 52	34. 8884
	0. 25 0. 50 0. 75	0. 251066. 090. 501232. 810. 751399. 52

