Actual Versus Perceived Energy Savings: Results from a Low-Income Weatherization Program

John Gardner and Lisa A. Skumatz, Skumatz Economic Research Associates, Inc.

ABSTRACT

Energy efficiency program evaluation relies on estimates of energy savings in order to draw reasonable and credible conclusions about the relative benefits of the improvements that programs implement. Common sources of estimates of energy savings are deemed savings, measured savings or self-reported savings

The authors decided to examine whether there were patterns in discrepancies between deemed and perceived savings that could be attributed to predictable factors, and identify whether (1) one measure can reasonably be used as a substitute for the other if one measure of savings is not available; and (2) whether these perceptions color the respondent's opinion of the energy efficiency measures, the program, and potentially, the utility itself.

We used a combination of utility-estimated energy savings data and phone survey data collected from participants in a state-wide low-income weatherization program in an attempt to identify important causes of discrepancies between utility-estimated and self-reported savings estimates. Using a series of statistical models of reported savings differentials, we found that demographic factors are not effective predictors of savings discrepancies. However, explanatory factors with substantial explanatory power were found, including the presence of program benefits above and beyond the cost savings on energy (non-energy benefits). Additional statistical analyses demonstrated that perceptions of high savings were correlated with high program satisfaction. The results indicate that a simple relationship between perceived and actual savings and easily identified exogenous variables may not exist. However, the work indicates there does appear to be a relationship between perceived energy savings, non-energy benefits, and program satisfaction.

Introduction

Estimates of energy (bill) savings for participants in household (and business) energy efficiency programs are crucial to the program evaluation process. Multiple techniques exist to collect such information: deemed savings, measured savings; and self-reported savings. Each savings estimate source has its own advantages and drawbacks. Deemed and measured savings estimates are, in general, more reliable. The utility can monitor energy use from a particular household both before and after the installation of energy efficiency measures. However, savings estimates obtained through the utility are expensive – they require additional attention to be paid to particular locations on the grid, and may necessitate the installation of additional monitoring devices. Confidentiality issues regarding private data also inhibit the effectiveness of utility-collected data. As a result, program savings are frequently provided by utility companies in terms of program aggregate savings, which are much less useful for evaluation and process research.

In contrast, self-reported savings estimates are comparatively inexpensive to obtain when program participants are already being surveyed with regard to other aspects of their experience with the program. Self-reported estimates, however, are less reliable, even when participants are explicitly aware that measures have been taken to improve the energy efficiency of their home.

The data show that average self-reported savings estimates can differ widely from average measured savings reports. Although the natural presumption is that measured estimates are more accurate, the discrepancies that arise between the two types of estimates are of intrinsic interest – they suggest that some individual characteristics, either demographic or related to the participant's experience with the program, create inaccurate perceptions of energy savings.

Only a handful of studies have directly addressed the issue of differential self-reported and actual data in environmental programs. An EPA study demonstrated that individuals tended to over-report vehicle miles traveled (Schipper and Moorhead 2000), while an Energy Information Administration study noted in passing that there were statistically significant differences between actual thermostat settings and those settings as self-reported by survey respondents (EIA 1996). Prior research has discussed the difficulties that arise when households attempt to quantify changes in energy use (Kempton 1984, Kempton and Montgomery 1982). The Kempton work. also highlights the role in quantifying energy use household perceptions of the amount of energy that different appliances consume, as well as the limitations of using energy bills, which aggregate all energy use into one number, in decomposing the effects of energy-conserving behavior on household energy use and costs. While previous research into the behavior and perceptual aspects of household energy management acknowledges that the household measurement of energy costs differs in both technique and result from expert energy analysis, this paper examines factors that may effect the direction and extent of that difference. This SERA-funded study (a) examines self-reported versus actual savings estimates in the context of energy efficiency programs and (b) attempts to discern the causes of any bias. The study was undertaken to:

- Examine if there are systematic and predictable patterns in the differences between perceived and actual savings; and
- Whether the perceptions color the respondent's opinion of the energy efficiency measures, the program, and potentially, the utility itself.

Data and Analysis

The first part of the analysis concentrated on identifying those factors that affect participant perceptions of energy savings delivered by program measures. The analysis used two data sources. The first is telephone survey data collected from a number of participants in a low-income weatherization assistance program in the Midwest. The program provided low-income (at or below 150% of the Federal Poverty Level) residents with energy-efficient and other weatherization-related household improvements in an effort to lower the energy costs faced by those participants. Ultimately, more than 300 surveys were completed by randomly chosen participants. Note that although our results do not show that income is a significant factor in contributing to the difference between actual and perceived savings, the conclusions drawn from those results should be viewed in the context of lower-income households.

Information was collected from program participants regarding:

1. Household demographics, including the number of overall household residents, the number of children, the number of elderly residents, the number of residents with chronic illnesses and the annual income of the combined household.
2. Changes in energy use and bills as a result of the program, including the extent to which energy use and bills changed, and the extent of that change.
3. Non-energy effects, including changes in home comfort, ability to pay energy bills, lighting quality, noise emitted by appliances, equipment maintenance, household aesthetics, understanding of energy use, equipment performance, calls to the utility regarding bills, payment or shutoff notices from the utility, environmental impacts, sick days, water bill costs, the frequency or intensity of chronic conditions such as asthma, the frequency or intensity of other illnesses, headaches, costs arising from doctor or hospital visits, medication costs and home safety.[1]

The second is a set of estimated savings estimates provided by the utility. Table 1 summarizes the results of utility-estimated and perceived savings by housing type. Our utility-estimated data consist of average by-household-type[2] energy savings values assembled from more individualized metering data collected from program participants before and after their dwellings were serviced by the program. We did not have access to participant-level savings data derived from meter measurements and assigned average utility-estimated savings by dwelling type to each respondent. Self-reported savings estimates in our sample vary widely around the estimates provided by the utility. However, as Table 1 demonstrates, the majority of participants gave self-reported savings that were generally much higher than the estimates provided by the utility.

Table 1. Summary of Perceived and Utility-Estimated kWh Savings

Variable	Obs	Mean
Perceived savings	167	486.6
Measured savings	362	201.5

It is important to note that both types of savings data are estimates. Throughout this paper, "self-reported" or "perceived savings" (or savings estimate) refers to answers given by survey respondents when asked a question of the form "How much did the program increase or decrease your energy bills?" Anecdotal evidence from interviewers indicates that in virtually all cases, responses were given from memory.[3] "Utility-estimated" savings (or savings estimate) refers to the average energy savings of households of a given type, as calculated by the utility.

---

[1] The non-energy benefits variables used in this analysis are simple categorical variables indicating respondents experienced positive, negative or no non-energy benefits. This survey technique has been described extensively in other papers by SERA. For a recent example, see Skumatz 2002.
[2] Single family home, apartment, mobile home or trailer, condo or town home
[3] In a few rare cases respondents may have referenced actual energy bills in order to provide savings estimates; however, the question asking for an energy savings estimate was only a minor question on the survey. It was a long survey, time was short, and respondents were not requested to find a bill. Because it was a relatively minor question, our dataset does not provide an indicator variable capable of distinguishing the few that may have had access to a bill.

Models of Discrepant Savings Estimates

That discrepancies will arise between savings estimates from metering data and self-reported accounts of energy savings is to be expected. Since self-reported savings estimates may be easier to obtain and free from the confidentiality requirements by which utility data may be bound, an examination of potentially predictable biases in self-reported data may be useful. Using the utility and survey data described above, we estimate several models of the biases in self-reported or perceived savings estimates.

Linear Models

The first set of columns in Table 2 (Model A) present the results from the first linear specification, in which we model the self reported-utility estimated savings differential (simply perceived minus utility-estimated savings) as a function of household demographic characteristics, the types of efficiency measures implemented through the weatherization program, and both health and non-health benefits beyond energy savings. To control for housing type without creating collinearity, we use (a) the number of units in the respondent's building and (b) the number of units in the building that underwent weatherization as proxies for housing-unit type in the models in Table 2.

Table 2. Detailed Specifications of Savings Differential Models (Linear and Logistic)

Dependent Variable	**Model A: Linear: Perceived minus utility estimated savings**		**Model C: Linear: Absolute value of perceived minus utility-estimated savings**		**Model C: Logistic: Dependent variable = 1 if perceived savings > utility-estimated; 0 otherwise**	
Regressor	**Coef.**	**t**	**Coef.**	**t**	**Coef.**	**z**
% of poverty level (direct proxy for household income)	104.90	0.86	56.25	0.53	0.635	1.47
No. of household residents	-45.18	-1.07	-25.91	-0.70	-0.196	-1.51
No. of children in residence	8.86	0.09	-23.92	-0.27	0.098	0.30
No. of elderly residents	-67.03	-0.70	-38.98	-0.46	-0.015	-0.04
No. of disabled residents	25.32	0.28	-15.74	-0.20	0.294	0.89
Units in building	-494.19	-1.04	54.63	0.13	-0.052	-0.19
Units weatherized	492.93	1.04	-65.76	-0.16	0.062	0.23
Number of measures installed	31.91	0.59	29.04	0.62	0.564	2.66
Heat measures installed	-61.76	-0.40	-70.85	-0.53	-0.913	-1.82
Insulation measures installed	-25.40	-0.16	-72.83	-0.52	-0.234	-0.51
Appliances installed	-11.69	-0.08	-55.27	-0.45	-1.165	-2.35
Health effects reported	169.50	1.49	45.47	0.46	0.359	0.88
Other non-energy benefits reported	692.38	3.06	-265.23	-1.34	1.073	2.13
Constant	-449.16	-1.47	812.12	3.04	0.344	0.42
Model "fit" statistics	F=1.95,Prob>F=0.03, R-squared= 0.149; Adj. R-squared=0.07; Root MSE=644		F= 0.43, Prob>F = 0.96, R-squared = 0.037, Adj R-squared = -0.05 Root MSE = 563		Number of obs = 343 LR chi2(13) = 22.79 Prob > chi2 = 0.0443 Pseudo R2 = 0.0908	

Although the regression itself has a statistically significant amount of explanatory power, the model performs poorly. It has an adjusted R-squared of only 0.07. However, it yields some insight into the determinants of differential savings estimates. The only explanatory variable in the model that is statistically significant from zero is "Other non-energy benefits reported," which is positive (t=3.06). In addition, the "Health effects reported variable" (t=1.49), while not significant and conventional confidence level, has the next-highest t-statistic and is also positive. These parameter estimates begin to suggest a pattern of higher biases in perceived savings estimates (relative to utility estimates) among respondents that either (a) accrued greater amounts of non-energy benefits or (b) were more satisfied with or enthusiastic about participating in the program (or vice versa).

The second column in Table 2 (Model B) presents the results from a second linear model, using the same specification but replacing the dependent variable with the absolute value of the difference between perceived and utility-estimated savings. This model has almost no explanatory power. None of its coefficients are statistically discernable from zero and its adjusted R-squared is actually negative. Jointly, the linear models presented in Table 2 suggest that, while program satisfaction can effect the direction of the bias in perceived savings estimates, it has little effect on their magnitude.

The models of savings differentials discussed above may be taxing for the already-noisy dataset to which they have been applied. As such, we also estimate both the perceived-actual savings differential and the absolute value of that differential as a function of a collapsed set of the variables used in the first two models. Specifically, we model each differential as a linear function of the number of units in the respondents building, the number of units subject to weatherization, the number of measures installed (which we use as a proxy for the extent of the weatherization service), whether the respondent reported any positive health effects as a result of the program, and whether they reported any non-health effects beyond energy savings.

As the first simplified model in Table 3 (model D) demonstrates, the savings differential model performs slightly better than the same model using the more detailed specification. The regressors used explain roughly 13% of the variation in the savings differential. Again, in this model, only the presence of non-energy benefits, health or otherwise, can be considered significant determinants of higher perceived vs. utility-estimated savings differentials.

Once again, when the same specification is used to model the absolute value of the savings differential, the significance of the regression vanishes. The second model in Table 3 (Model E) shows that our model of absolute savings differentials as a function of the collapsed set of explanatory variables described above has almost no explanatory power or significant coefficients.

Table 3. Collapsed/Simplified Specifications of Savings Differential Models (Linear and Logistic)

Dependent Variable	Model D: Linear: Perceived- minus utility estimated savings		Model E: Linear: Absolute value of perceived minus utility estimated savings		Model F: Logistic: Dependent variable = 1 if perceived savings > utility-estimated; 0 otherwise	
Regressor	**Coef.**	**t**	**Coef.**	**t**	**Coef.**	**z**
Units in building	-519.42	-1.12	36.14	0.09	-0.034	-0.13
Units weatherized	519.07	1.12	-45.98	-0.11	0.045	0.17
Number of measures installed	14.13	0.40	4.32	0.14	0.146	1.23
Health effects	170.91	1.61	43.11	0.47	0.344	0.89
Other non-energy benefits	717.85	3.32	-254.73	-1.35	0.993	2.10
Constant	-509.94	-2.16	698.05	3.40	0.481	0.86
Model "fit" statistics	F = 4.68 Prob>F = 0.0005 R-squared = 0.1326 Adj R-squared = 0.1042 Root MSE = 633		F = 0.77, Prob>F = 0.5700 R-squared = 0.0247 Adj R-squared =-0.007, Root MSE = 552		LR chi2(5) = 8.37 Prob>chi2 = 0.1368 Pseudo R2=0.0334	

Logistic Models

The OLS models discussed above paint a picture of the self-reported vs. utility-estimated savings differentials in which the direction of biased self-reports of energy savings are predictable, but the magnitude of the bias is not. Models of the absolute value of the difference between perceived and utility-estimated savings – however specified – have little or no explanatory power.

To further investigate potential causes of biased or discrepant self-reported savings estimates compared to deemed estimates, we estimate a series of logistic regressions that model the odds of perceived savings estimates being greater than utility-estimated savings as a function of the variables used in specifications one and two from the previous section.

The last model presented in Table 2 above (Model C) provides a summary of the first such model. Unlike the OLS regressions above, this model only accounts for whether self-reported savings exceeds utility-estimated savings. As such, it is less sensitive to random variation in self-reported savings estimates. This decreased sensitivity to dependent-variable variation makes basic effects related to the particular types of measures installed through the weatherization program more easily discernable. For example, the number of measures implemented and whether those measures were related to heating or appliances were significant determinants of the direction of the self-reported savings bias.

However, although the number of measures implemented overall make an overestimate more likely, the presence of measures related to heating or appliance replacement appear to make an overestimate significantly less likely. Although this pattern may be due to any number of underlying causes, the most direct explanation is that program participants that receive newer or more effective heating measures or appliances are likely to use those measures more, especially in the time period after they have just been installed. Such behavioral changes might lead to higher energy bills and a perception of increased energy costs.[4]

Nevertheless, the presence of non-energy benefits was again a significant determinant of the direction of the bias in self-reported savings. Respondents that reported experiencing positive non-energy benefits were much more likely to over-report their energy savings relative to utility-estimated savings.

Finally, we use the same binary dependent variable with the collapsed second specification used for the OLS regressions. This result is presented as the last model in Table 3 (Model F). Under this specification, the only significant determinant of the direction of the bias in self-reported savings estimates is the presence of non-energy benefits.

Detailed Discussion of Findings

Summary of Findings

The models of discrepancies in self-reported compared to utility-estimated savings presented above suggest several conclusions about the nature of energy savings as they are perceived by participants in energy efficiency programs. We presented models of both the difference between perceived and utility-estimated savings and the absolute value of that difference. Each variable was modeled using two specifications: (a) an expanded specification, which treated the differential as a function of household-specific demographic characteristics, the number of units, the number of units subject to weatherization, the number of measures implemented, dummy variables for the presence of heating, insulation or appliance measures, and the presence of health or non-health benefits beyond energy savings; and (b) a collapsed specification, which treated the differential as a function of the number of units in the applicable building, the number of units subject to weatherization, the number of measures installed and the presence of either health or non-health benefits beyond energy savings.

The regressions that modeled the simple difference between perceived and utility-estimated savings showed that the differential was insensitive to most demographic and program characteristic variables. Household structure variables, such as the number of residents, the number of children, etc. had no demonstrable effect on the savings differential. Neither did most of the program characteristic variables, such as the number or types of measures installed. The only variables that were significant determinants of the savings differential at standard levels of statistical certainty were dummy variables designed to indicate the presence of non-energy benefits. In both models, the marginal effect of non-health non-energy benefits was on the order of $700.

Neither of the regressions that modeled the absolute difference between perceived and utility-estimated savings could be shown to be statistically different from the hypothesis that all of the slope parameters were equal to zero. These models exhibited poor fit statistics, implying that the magnitude of savings differentials is unrelated to the factors used as explanatory variables.

Finally, logit models of the probability that perceived savings exceed utility-estimated savings were run, using similar specifications to the other models. In each of these models, the

[4] See Kempton (1982) for an interesting discussion of perceptual aspects of energy use and the conflation by households of concurrent changes in energy use and energy price.

presence of non-energy benefits was again a substantial determinant of a positive bias in self-reported energy savings.

The OLS models demonstrate that, while the direction of the bias in self-reported savings is predictable to a degree, the magnitude of that bias is not. Regardless of the specification used, models of the absolute difference between self-reported and utility-estimated savings showed little or no explanatory power.

The only regressors that are capable of explaining a substantial component of the direction of the bias between perceived and deemed savings are those related to non-energy effects associated with program – whether the participant experienced either health or non-health benefits beyond energy savings as a result of the measures implemented in their household through the program, above and beyond cost savings on energy. This pattern of the explanatory power of NEBs suggests, on face, that a higher level of satisfaction with the program as a whole may cause participants to positively bias their savings estimates.[5]

Caveats

It is possible that the consistent significance of the non-energy benefits variables included in the regressions is due to a latent connection between higher-than-average energy savings and the presence of non-energy benefits. For example, if recipients of appliances of a particular brand are more likely to have reported both high energy savings and positive non-energy benefits, it could be that appliances of that brand offer higher levels of both energy savings and non-energy benefits.

We have attempted to control for such an effect. In the two specifications used for both OLS and logit models, we control for the number of measures implemented as well as the types of measures implemented. Our dataset does not contain any information about the measures implemented beyond their type and number, so it is not possible to control for brand, model or other more specific measure characteristics.

Additionally, although the effect on biased savings estimates for non-energy benefits is consistent throughout the models estimated, none of the models perform especially well. Both of the logit models and each of the OLS models that use perceived minus deemed savings as the dependent variable have statistically significant fit statistics, but explain only a minority of the variation in the difference between measured and perceived savings. Part of this lack of "fit" is a result of the fact that self-reported savings estimates, usually given from memory, are likely to contain a large random error component.[6]

Not everyone monitors their electricity bill closely, and not everyone monitors changes in their energy bill after the installation of energy efficiency measures. However, the lack of explanatory power in the regressions may also be due to the absence of other important variables

[5] Unfortunately, explicit program satisfaction questions were not asked as part of this survey, so further investigation of the relationship between satisfaction, perceived savings estimates and non-energy benefits is not possible. This will hopefully be a topic for future SERA research.

[6] An anonymous reviewer suggested that another way to look at this is that, based on Kempton and Montgomery 1982, people understand their bills differently than experts do. The authors note that the issues being addressed are different. Understanding a bill differently, as Kempton argues, involves using different units to quantify total energy use – looking at price, for example, instead of kWh. This problem doesn't arise here, because we are comparing self-reported savings against savings as calculated using the measured energy (unit) savings times the given price per kWh (and Btu.).

that are uncorrelated with the regressors already included. If this is the case, the ability to predict patterns in self-reported savings biases may be greater than the models above indicate, and work is being undertaken to try to gather additional data to identify these missing factors.

It may be the case that the significance in determining differential savings estimates of non-energy benefits is a symptom of high levels of program satisfaction interfering with the energy savings estimation process in phone interviews. If this is the case, detailed questions about program satisfaction, both overall and with respect to specific program components, may be useful in controlling for a satisfaction-savings bias effect.

The results imply that, although the direction of the perceived vs. utility-estimated energy savings differential is predictable to a degree, this research indicates that the magnitude of this differential is not. This outcome is a mixed blessing for the purpose of program evaluation. The lack of factors that correlate with the size of the self-reported energy savings bias means that steps to reduce that bias may be difficult to find. On the other hand, researchers do not need to worry that particular demographic or program characteristics will cause outliers in savings estimates.

Finally, as mentioned earlier, the sample of participants in our study is comprised of households at 150% of less of the Federal Poverty Line. The energy-efficiency measures that were implemented in their homes via the program were targeted specifically at reducing energy (and water) bills, and they were not charged for the modifications that were made. The dynamics of the relationship between deemed savings, utility-estimated savings, and participant demographic characteristics may differ for low-income participants compared to program participants that undertake energy efficiency improvements under different circumstances – especially if money is exchanged for those improvements. Additional work is being undertaken to further explore these effects and to examine the role of attitudes (specifically “self-efficacy”) in these differences.

Next Steps

The results of this study are intriguing, but are exploratory and should not be generalized beyond the low income weatherization situation. However, the opportunity for expanded study of perceived vs. utility-estimated savings differentials is great. Studies comparing utility-estimated results from programs with different populations but comparable measures have the potential to further explore the relationship between population characteristics and patterns in savings estimate bias.

Additionally, further work in this area should attempt to control more closely for specific program characteristics, such as the brand, model, size, etc. of measure implemented to eliminate concerns about hidden relationships between non-energy effects, program satisfaction and energy savings. Any work that utilizes household-specific metering data – combined with questions about changes in the use of equipment – will be able to form a finer picture of the relationships between the factors considered in this paper. Because one potential source of bias in perceived savings estimates is enthusiasm about or satisfaction with program participation, laboratory-style experiments may be helpful in controlling for the relationship between satisfaction and savings overestimation.

In addition, it may be useful to explore the potential of attitudes, and in particular self-efficacy factors, in helping explain more of the variation in differences between perceived and actual savings.

Summary and Conclusions

The authors analyzed data from a statewide low income program to determine if there were patterns in discrepancies between utility-estimated and perceived savings that could be attributed to predictable factors, and identify whether (1) one savings measure can reasonably be used as a substitute for the other if one measure of savings is not available (or to reduce evaluation costs); and (2) whether perceptions color the respondent's opinion of the energy efficiency measures, the program, and potentially, the utility itself.

Variability in self-reported savings estimates is to be expected, and the analyses show that we can draw some interesting and potentially useful conclusions about the nature of that variability. First, using OLS and logit models, we found that demographic factors are not effective predictors of savings discrepancies. However, explanatory factors with substantial explanatory power were found, including the presence of program benefits above and beyond the cost savings on energy (non-energy benefits), and to a lesser degree, health effects from the program. The OLS and logit models described demonstrate that the presence of non-energy benefits associated with program participation is a significant determinant of a higher-than-estimated perceived savings estimate. In particular, participants that experienced such an effect quoted annual savings estimates that were considerably higher than measured savings, on average. Additionally, the presence of such non-energy effects substantially increased the odds that a respondent would present a perceived savings estimate that exceeded the estimate generated by the utility company.

The ability to predict the direction of biases in perceived savings estimates suggests some ability to correct for those biases. If it is believed that non-energy benefits should be uncorrelated with energy savings for a particular program, one possibility is simply to remove the estimated savings differential that can be attributed to the non-energy benefits variable. However, due the fact that the explanatory power of the models was low, it does not appear that perceived savings can "stand in" for actual savings, or vice versa – at least until better models and explanatory factors are identified. To this end, additional work will be pursued on the role of attitudes and other data to further explore their applications in understanding drivers of the relationship of perceived vs. actual savings and program satisfaction.

References

EIA (U.S. Department of Energy, Energy Information Administration). 1996. "Residential Energy Consumption Survey Quality Profile." Available online at <http://tonto.eia.doe.gov/FTPROOT/consumption/0555961.pdf>.

Kempton, Willet and Laura Montgomery. 1982. "Folk Quantification of Energy." *Energy*. 7(10): 817-827.

Kempton, Willet. 1984. “Residential Hot Water: A Behaviorally Driven System.” In Proceedings from the ACEEE 1984 Summer Study on Energy Efficiency in Buildings, Washington DC, American Council for an Energy Efficient Economy.

Schipper, Mark and Vicki Moorhead. 2000. “Odometer Versus Self-Reported Estimates of Vehicle Miles Traveled.” Available online at < http://www. eia.doe. gov/ emeu/ consumptionbriefs/transportation/vmt/vmt.html>.

Skumatz. 2002. ” Comparing Participant Valuation Results Using Three Advanced Survey Measurement Techniques – New Non-Energy Benefits (NEB) Computations of Participant Value”, Asilomar, California: Proceedings of the 2002 ACEEE Conference. Washington DC, American Council for an Energy Efficient Economy.

Skumatz, Lisa A., Ph.D, and John Gardner, 2006. “Differences in the Valuation of Non-Energy Benefits According to Measurement Methodology: Causes and Consequences”, Proceedings of the Association for Energy Service Professionals NESP Conference San Diego, CA, AESP, Clearwater FL.