Attributing NEB Values to Specific Measures: Decomposition Results from Programs with Multiple Measures

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ABSTRACT

Most non-energy benefits (NEB) work has estimated NEBs at the program level. This study re-examines NEB results for programs with multiple measures and "packages" of measures or interventions. The research used statistical models to decompose the program NEB values and "assign" portions of the NEB values to individual measures. The work examined data from a low income weatherization program. The work provides long-missing results on the impacts of individual measures on the value of programs.

The research provides information on the NEBs associated with individual measures rather than addressing NEBs largely at the program level. These results will help program staff use the results for optimizing program design, and identifying those measures with greatest value to participants. This paper provides a previously ignored enhancement to NEB research, and provides specific NEB results for a set of residential measures, and has been applied for both residential and commercial measures.

Introduction

Broadly, non-energy benefits are effects associated with energy-efficiency or related programs or measures that arise in conjunction with, but not because of, decreased energy use or spending on energy.[1] Non-energy benefits arise from a wide range of the characteristics of the equipment with which they are associated. Less space used by a new, high-efficiency boiler, for example, might be considered such a benefit, as might reduced household noise as a result of increased insulation.[2]

The applicability of non-energy benefits research and valuation to the program evaluation process is obvious – any analysis of the relative costs and benefits of an energy-efficiency program can include the non-energy benefits of the measures implemented by the program. The inclusion of non-energy benefits in this type of work is becoming increasingly common, as program administrators and evaluators continue to embrace non-energy benefits as a valid class of effects that should be considered in any holistic view of an efficiency program. Furthermore, the inclusion of non-energy benefits in valuation studies shows that they add a substantial amount of value, not just to participants, but socially (Skumatz and Dickerson 1997, Imbierowicz and Skumatz, 2004, Schweitzer and Tonn 2002).

However, the use of non-energy benefits in program evaluation work limits the breadth of their applicability to ex post analysis. Most evaluation research that includes non-energy benefits is done after the initial implementation of the relevant program. While this type of analysis is

[1] Technically, non-energy benefits may be either positive or negative, and the net non-energy benefit is the sum of all benefits incurred (either positive or negative). Since, in most cases, net non-energy benefits are positive, we use the term non-energy benefits to represent the sum of all positive and negative effects.
[2] For a more complete introduction to non-energy benefits, see Skumatz and Dickerson 1997.

useful, it is far from the only way in which non-energy benefits research can be used. Especially in a context in which program planners and administrators are explicitly aware of the non-energy aspects of their programs during planning and setup stages, prior non-energy benefits research may be useful as a program design tool. Given that the presence of non-energy benefits can drastically increase the value assigned by participants to the program, selecting measures that have empirically been valued highly represents an opportunity to optimize program effects with respect to both energy and non-energy benefits.

Moreover, non-energy benefits can be used as a selling strategy (Skumatz and Gardner 2005, Pearson and Skumatz, 2002, McHugh et al. 2002). Coupling energy savings with other benefits like increased home aesthetics and comfort, greater occupant productivity, better occupant health, and lower maintenance costs, may stabilize the demand for energy efficiency programs, which may fluctuate based on current energy prices. In this light, knowledge of the energy efficiency measures that contribute the most to total non-energy benefits, or knowledge of approximately how big a contributor each measure is, can play a role in choosing the total package of measures that will be offered through a program. In private programs, there may be instances where it makes sense to include efficiency measures that are known to cause high levels of non-energy benefits, even if their contribution to energy efficiency is marginal – customers may be more attracted to the total package.

A shift towards including pre-program estimates of non-energy benefits as part of the program design process, however, requires a great body of prior empirical work regarding the expected level of non-energy benefits that different measures will produce. This requirement has two immediate consequences:

1. Ex post non-energy benefits valuation work needs to attempt to discern the total level of non-energy benefits, as well as the level of benefits that arise due to particular program aspects or measures.[3]
2. The level, or at least direction, of non-energy benefits that might be attributable to different measures should be cataloged by firms and organizations that implement, design or sell energy efficiency programs or packages, and would need to be updated on an ongoing basis to reflect changes in technology or consumer taste.

The task of determining how much of the non-energy benefits associated with a multifaceted, multi-measure efficiency program owe to each measure or intervention comprising the program may be a daunting one. Respondents are already asked to estimate the degree to which the program measures, taken together, caused particular kinds of non-energy benefits –

[3] We are reminded by an anonymous reviewer that in addition to knowing *how much* benefit each measure produces, it may also be useful to know *why* each measure produces that benefit. Determining the origin of a non-energy benefit usually involves either (a) asking respondents to explain why they felt that a measure was beneficial or (b) performing laboratory tests on readily measurable non-energy aspects of equipment (noise output, for example). Measure-level non-energy benefits valuation is conceptually separate from benefit source identification. Both can be used simultaneously, and in fact, each complements the other. The fact that NEBs emanate from energy efficiency measures was discussed in the literature throughout the late 1980s and early 1990s (this can be seen in the references included in Skumatz and Dickerson 1997); however, this earlier work focused on proposing lists of benefits and possible associations with measures, and did not quantify any impacts. Our purpose in work since has been to measure those effects, and in this paper, we focus on determining which measures create the most value in terms of non-energy benefits, regardless of how or why they do so. The manner in which our questions ask about the NEBs asks specifically whether the measures themselves provided any NEBs. Thus, for the purposes of the discussion below, the benefit source identification has already been performed by the respondent.

better maintenance, increased comfort, helping the environment, etc. To ask, in addition, how much of that benefit is due to each particular energy efficiency measure that they received through the program may put an undue burden on survey respondents. There is no guarantee that program participants will be able to assign how much of the increased comfort in their household is due to their new air conditioner and how much is due to upgraded insulation, for example, with any degree of certainty.[4]

A more accurate accounting of the sources of the non-energy benefits reported, therefore, is likely to come from post-survey analysis of the data. The methods used to accomplish this object, however, may differ, depending on the structure of and methods implemented via the program. When program participants are asked the extent to which they experienced fewer headaches as a result of program participation, it should be clear that any related effect is due to changes in household lighting, rather than window caulking. But when participants claim that they experienced non-energy benefits related to greater home aesthetics, it may not be possible to differentiate between increases in aesthetics caused by better lighting, newer, more attractive appliances, or another latent cause.

In such cases, where non-energy benefits are reported but are not obviously attributable to specific measures, more sophisticated measures may be required to decompose the sum of non-energy benefits into those caused by specific measures. In this paper, we use data from an extensive weatherization assistance program to outline some methods for by-measure decomposition of non-energy benefits. Section two provides a brief description of the program and its participants, section three demonstrates the use of econometric models to analyze the components of non-energy benefits by measures implemented, and section three discusses and concludes.

Data and Descriptive Statistics

We use data collected via phone surveys from participants in a statewide low-income weatherization assistance program. Residents at or below 150% of the Federal Poverty Level for their household size were eligible to participate. Together, 362 participating households were surveyed.

Table 1 presents a demographic summary of the households in our sample. Household incomes range from none to $63,000 annually; number of residents ranges from one to eleven, (with an average of 2.5). Table 1 also characterizes the housing situations of those surveyed. The majority of the participants contacted for the survey owned single family houses. Multifamily units with between two and four units were the second most common housing type, although housing ownership more than twice as common as renting.

[4] Clearly if respondents participated in programs that implemented or supplied only one efficiency measure, 100% of the reported non-energy benefits can be attributed to that measure. In such cases, the task for application to future programs is indexing the measures received by participants in such a way that they can be easily compared. For example, data from an energy-efficient lighting program should include variables that capture the type of light bulbs or lamps installed, so that the non-energy benefits values might be adjusted appropriately for comparison with other equipment types or brands.

Table 1. Demographics and Number of Measures Installed

Variable	Mean
Household income	14,230
Number of residents	2.51
Number of children	0.35
Number of elderly residents	0.46
Number of disabled residents	0.43
Percent SF	58.8%
Percent in 2-4 unit dwelling	19.9%
Percent in Apartment/multi-unit	8.8%
Percent in Mobile Home or Trailer	12.4%
Percent owning home	74.3%
Percent renting	25.7%
Number of measures: Only original measures[5]	3.63
Number of measures: All measures[6]	5.33

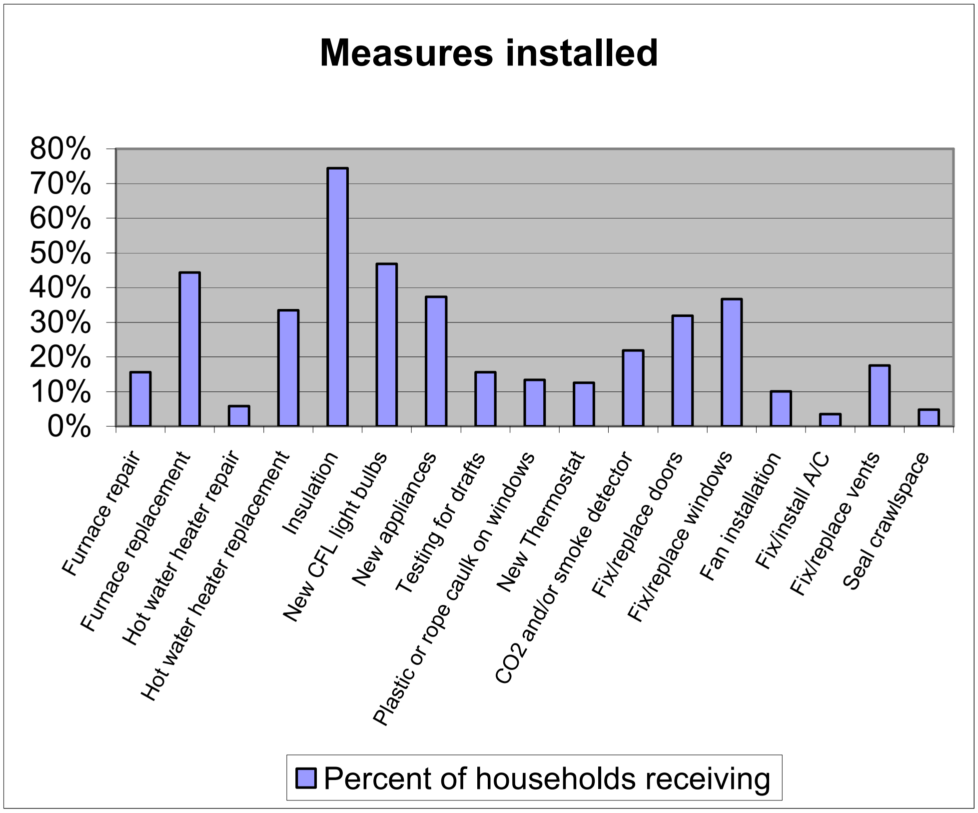
Table 1 and Figure 1 characterize the number, types and distribution of measures installed via the program. On average, 5.3 measures were installed in each household, including energy-efficiency, water efficiency, and health and home safety measures. Each household received at least one and at most ten such measures.

Insulation was the most common measure, and was installed in 74% of participating households. Furnace replacement and the provision of CFL light bulbs were the next-most common measures, and were installed in 44% and 47% of households, respectively.

[5] Certain measures were added after the program began servicing homes. The first row summarizes only the originally available measures. The initially available measures included furnace repair and replacement, hot water heater repair and replacement, insulation, new CFL light bulbs, new appliances, draft testing, plastic or rope caulk on windows and new thermostats. The program's measures were expanded to include CO2 and smoke detectors, fixed or replaced doors, windows, air conditioners and vents, fan installation, and crawlspace sealing. Obviously, participants whose homes were serviced later in the program were more likely to receive more measures. A minimum of zero of these measures, and a maximum of 8 of these measures were installed in our sample.

[6] A minimum of 1 and a maximum of 10 of these measures were installed in our sample.

Figure 1. Percent of Households Receiving Each Measure



In terms of energy use and cost, the net effect of the measures installed through the program was positive. The majority of participants noticed a decrease in their energy use, and about 20% thought that it decreased significantly (Table 2). Similarly, most participants perceived a decrease in their energy bill. According to metering data, the average annual energy savings associated with the program were about $200 per household.

Table 2. Changes in Energy Use and Cost

Percent Reporting level of change in:	Energy Use	Energy Bills
Increased a lot	2.4%	2.5%
Increased somewhat	5.7%	5.2%
Stayed the same	27.7%	30.2%
Decreased somewhat	43.5%	47.4%
Decreased a lot	20.8%	14.8%
Total	100%	100%

More important for the purpose of this paper are the non-energy benefits associated with program participation. The authors used a labeled magnitude scaling[7] technique to assess both (a) the general direction and (b) dollar estimates of the non-energy benefits that accrued to program participants. Respondents were first asked whether they experienced negative, positive or no

[7] In fact, several non-energy benefits valuation techniques were applied to the data, including variations on the labeled scaling approach as well as other direct valuation approaches such as willingness to pay and willingness to accept scenarios. The net non-energy benefits values used for this analysis come from the scaling approach, which we found to produce the most reasonable results. See Skumatz 2002.

effects with respect to both individual categories of non-energy benefits and non-energy benefits in aggregate. They were then asked to value those benefits relative to the energy savings that they experienced.

As Table 3 demonstrates, the vast majority of participants reported experiencing some level of non-energy benefit as a result of the program. About 8% reported no effect, and 2% reported a negative effect. The valuation method estimated a combined non-energy benefit of about $231 per household annually.

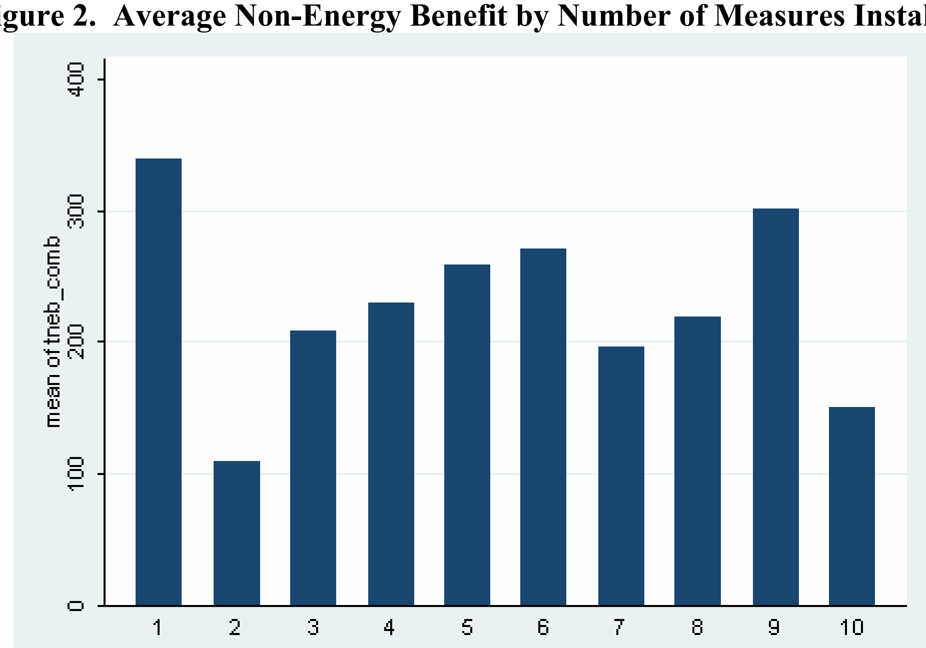
Table 3. Direction of Non-Energy Benefits (NEBs)

Direction	Percent
Negative	2.3%
No effect	8.2%
Positive	89.6%
Total	100%

Regarding the relationship between non-energy benefits and the measures from which they arise, an obvious question is whether the sheer number of efficiency measures drives non-energy benefits up. Figure 2 shows that, in our sample, the greatest average non-energy benefits value arises among participants that received only one measure – suggesting not only that not all efficiency or other measures produce non-energy benefits, but that certain measures produce them in greater quantity than others.

However, in order to better understand the relationship between energy efficiency measures and non-energy benefits, it is necessary to be able to discern the effect of (a) the number of measures installed, (b) the kinds of measures installed as well as (c) the magnitude of the effect of each type of measure. In the following section, we use several models of non-energy benefits to further explore that relationship.

Figure 2. Average Non-Energy Benefit by Number of Measures Installed



Econometrics

In order to distinguish between the effects of the number of measures installed, the specific types of measures installed and the demographic characteristics of the households that participated in the program, on the value of the non-energy benefits reported by those households, we estimate two models of non-energy benefits. The results of both these models are provided in Table 4.

Model 1, below, treats non-energy benefits as a function of participant characteristics and measures installed. The model is estimated by OLS.[8]

Table 4. Results from Models to Distribute Non-Energy Benefits Across Measures: Results for Linear and Logit Modeling (bold indicates 85% significance or better)

	Model 1: Linear Model			Model 2: Logit Model		
Parameter	**Coef.**	**t**[9]	**P>|t|**	**Coef.**	**z**	**P>|z|**
Furnace repair	**207.3**	**1.98**	**0.05**	37.0	0.00	1.00
Furnace replacement	98.1	0.87	0.39	0.3	0.40	0.69
Hot water heater repair	132.1	0.64	0.52	35.9	0.00	1.00
Hot water heater replacement	-40.1	-0.34	0.73	-1.0	-1.42	0.16
Insulation	**288.4**	**2.88**	**0.01**	**1.2**	**2.04**	**0.04**
New CFL light bulbs	-129.0	-1.28	0.20	-0.3	-0.45	0.65
New appliances	111.2	1.08	0.28	0.2	0.22	0.82
Testing for drafts	63.2	0.42	0.68	**2.3**	**1.48**	**0.14**
Caulk on windows	109.0	0.84	0.40	0.04	0.04	0.97
New Thermostat	-178.7	-1.39	0.17	0.03	0.03	0.98
CO2 and/or smoke detector	7.3	0.06	0.95	0.07	0.08	0.93
Fix/replace doors	0.5	0.00	1.00	-0.7	-1.02	0.31
Fix/replace windows	71.6	0.79	0.43	-0.9	-1.41	0.16
Fan installation	-105.0	-0.60	0.55	**-2.0**	**-2.33**	**0.02**
Fix/install A/C	-285.7	-1.32	0.19	35.9	0.00	1.00
Fix/replace vents	-152.7	-1.12	0.27	-1.0	-1.26	0.21
Seal crawlspace	11.4	0.05	0.96	-1.0	-0.80	0.42
Household income	**0.01**	**1.62**	**0.11**	**-0.0**	**-2.68**	**0.01**
Number of residents	-19.9	-0.46	0.65	**0.6**	**1.82**	**0.07**
Number of children	**144.5**	**1.52**	**0.13**	0.2	0.46	0.65
Number of elderly residents	**-129.5**	**-1.91**	**0.06**	**0.9**	**1.43**	**0.15**
Number of disabled residents	67.7	0.83	0.41	0.8	1.25	0.21
Constant	186.6	1.14	0.26	-3.8	n/a	n/a
Intercept 2	n/a	n/a	n/a	-2.1	n/a	n/a
Model "Fit" Statistics	F=2.18, Prob>F=0.0049			LR Chi2=31.45, Pr>Chi2=0.0873		

The results from model 1 demonstrate that, in our sample, households that received insulation valued the non-energy benefits that they received at an average of $288 greater than those that did not. The results show that none of the remaining measure dummy variables were statistically significant; although there was a trend towards negative effects with new thermostats

[8] Specifically, the model is specifed as $NEB=a+\Sigma_j b_j X_j+\Sigma_k c_k Y_k+e$, where NEB is total non-energy benefits, X_j represents the jth efficiency measure, Y_k represents the kth demographic characteristic, and e is the error term.

[9] Robust standard errors were used. A Breusch-Pagan heteroscedasticity test was highly significant ($P > \chi^2 = 0.0156$).

and air conditioner installation and repair, the parameter estimates on these variables failed to meet conventional levels of statistical significance.

The demographic variables used in model 1 were also unrelated to total non-energy benefits. Household income appeared to have a slightly positive effect, though negative values are well within the 95% confidence interval (-.002 to .022). The number of children residing in the household appeared to increase non-energy benefits, though not at reasonable significance levels (p=0.13). The number of elderly residents (>65 years), however, significantly reduced non-energy benefits, by an average of $129 per older resident.

Although the fit statistics for model 1 were reasonable, the specification may be too demanding for the data. The non-energy benefits values are created through a multiple step process from initial survey data, and each step possibly increases the error of the point estimates. Combined with the large number of covariates used in the model, there is a good chance that subtle effects in variations of non-energy benefits values are obscured.[10]

To this end, we also estimate a logit model of the direction of non-energy benefits (negative, none or positive), using the same specification as that used for model 1.[11] Table 4 also summarizes the statistical results for Model 2, the logit model. .

In our logit model, whether a participating household received insulation through the program was again an important component of non-energy benefits; the estimate indicates that insulation increased the odds of a higher NEBs rating (from negative to zero, or from zero to positive) substantially. The only other measure related variable that had a statistically significant result in this model was fan installation, which made lower non-energy benefits ratings more likely. Household income has a statistically significant, yet small, negative effect, and each household resident made a higher non-energy benefits rating more likely.

Discussion and Conclusions

We have presented two models of the non-energy benefits associated with a low-income weatherization assistance program as a function of some demographic characteristics of the program's participants, and the measures that those participants received in their homes through their participation. The results from those models suggest that, among the measures installed through the program, insulation was a very important determinant of the sign and amount of non-energy benefits reported by those surveyed, contributing, according to our OLS model, about $288 US to the value of the non-energy benefits claimed.

In these exploratory results, none of the other measures had systematic effects on non-energy benefits in both of the models that we used, although having a fan installed seemed to have a significant negative effect in the second model, perhaps indicating an issue with noise. Demographic factors were not especially important, either, although there may be a slight negative correlation with household income.

Nevertheless, the absence of significant model coefficients does not imply that the remaining measures implemented through the program do not cause non-energy benefits, but that, with the exception of insulation, none of the measures are responsible for more than their share of variation in total non-energy benefits. Moreover, non-energy benefits may arise through

[10] The authors are re-running different specifications of the models for future analyses.

[11] Model 2 is a proportional-odds logit model. This model takes the basic form $\ln(\text{odds}(y=k|x) = \tau_k - x\beta$, where y is a discrete response variable with 3 categories indexed by k (positive, no, or negative non energy benefits), and x is a vector of explanatory variables (measures installed and household demographic characteristics).

the interaction of measures – several heating and appliances measures, together, may cause increased perceptions of home comfort. Our data were not sufficiently robust to allow for the demands of that many interaction terms.

The analysis presented in the previous section demonstrates both the difficulty and importance of by-measure non-energy benefits attributions. Although we expected some of the measures implemented in the study, like air conditioner installation or new appliances, to yield a great deal in non-energy benefits through their effects on home comfort and beauty, neither appeared to be significantly related to either the dollar value the non-energy benefits or if those benefits were positive, neutral or negative. At the same time, the overwhelming importance of insulation illustrates how simple energy efficiency measures can add a great deal of value to programs, above and beyond cost savings on electricity.

For programs where only one (or just a few) measures have been installed, multivariate statistical techniques may not be necessary in order to decompose non-energy benefits. If phone interviews are used to gather data, the addition of a few questions regarding which measures were the most important, or which measures contributed to which types of non-energy benefits, is marginal. On the other hand, econometric techniques may very well be easier to apply to datasets that involve fewer measures, and the use of several techniques may give rise to different perspectives about the sources and magnitudes of benefits, and may lend additional insight into apparent anomalies or unsuspected relationships between variables.

Summary and Implications

These exploratory results indicate that the statistical decomposition of NEB results into their "causal" measures or interventions is a promising technique. The analysis presented in this paper demonstrates a method that can be used to identify which measures are most effective in delivering NEBs and whose effects are most (positively) noticed by residents (and, for other work, employees in commercial buildings). These results will provide feedback allowing utilities to identify – and promote – high-NEB measures in their programs. They provide information to allow programs to increase the "bang for the buck" by including high-performing NEBs in a higher percent of participant buildings, if appropriate.

On-going work is examining commercial programs, running models including "packages" of measures to improve statistical properties and explanatory power, and separately examining the impacts of positive and negative NEBs.

References

Imbierowicz, Karen and Lisa A. Skumatz, Ph.D., "The Most Volatile Non-Energy Benefits (NEBs) – New Research Results "Homing In" on Values for Environmental and Economic Impacts", Proceedings of the 2004 ACEEE Summer Study, Asilomar, CA, August 2004.

McHugh, Jonathon, Lisa Heschong, Daryl Mills, Cosimina Panetti, Nehemiah Stone and Abby Vogen. 2002. "Non Energy Benefits as a Market Transformation Driver." ACEEE Summer Study on Energy Efficiency in Buildings. Available online at: http://www.energy. ca.gov/papers/2002-08-18_aceee_presentations/PANEL-06_MCHUGH.PDF

Pearson, Dennis, and Lisa A. Skumatz, Ph.D., "Non-Energy Benefits Including Productivity, Liability, Tenant Satisfaction, and Others: What Participant Surveys Tell Us About Designing and Marketing Commercial Programs", Proceedings of the 2002 ACEEE Summer Study on Energy Efficiency in Buildings, Asilomar, Washington, DC, August 2002.

Schweitzer, Martin and Bruce Tonn. 2002. "Non-energy benefits from the Weatherization Assistance Program: A Summary of Findings from the Recent Literature." Available online at: http://www.osti.gov/bridge. Oak Ridge, TN.

Skumatz, Lisa A., "Comparing Participant Valuation Results Using Three Advanced Survey Measurement Techniques: New Non-Energy Benefits (NEB) Computations of Participant Value", Proceedings of the 2002 ACEEE Summer Study on Energy Efficiency in Buildings, Asilomar, Washington, DC, August 2002.

Skumatz, Lisa A., and Chris Ann Dickerson, "Recognizing All Program Benefits: Estimating the Non-Energy Benefits of PG&E's Venture Partner Pilot Program (VPP)", 1997 Energy Evaluation Conference, Chicago, August 1997.

Skumatz, Lisa A., Ph.D. and John Gardner, "Methods and Results for Measuring Non-Energy Benefits in the Commercial and Industrial Sectors", Proceedings of the ACEEE Industrial Conference, West Point New York, July 2005.