A Meta-Analysis of Drivers of Freeridership in Appliance Recycling Programs

Josh Keeling, The Cadmus Group, Portland, OR
Kate Bushman, The Cadmus Group, Portland, OR

ABSTRACT

Typically, appliance recycling programs prove very cost-effective and serve to introduce energy efficiency for utility customers. However, very high freeridership may cause utilities to reexamine these programs' validity. Given the widespread acceptance of the California self-report methodology, first introduced in the 2002–2003 Statewide Evaluation, these programs' net-to-gross findings have a cross-comparability level not often found in other programs. In this paper, we conduct a meta-analysis of widespread data available on freeridership in appliance recycling programs to identify freeridership drivers for these programs. Achieving a deeper understanding of the reasons why freeridership varies can aid utilities in making informed decisions about program design.

Introduction

Typically, appliance recycling programs (ARPs) prove a very cost-effective way to introduce energy efficiency for utility customers. However, very high freeridership may cause some utilities to reexamine these programs' validity. Given the widespread acceptance of the California self-report methodology, first introduced in the 2002–2003 Statewide Evaluation, the programs' net-to-gross findings have a greater cross-comparability level not often found in other programs. In this paper, we conduct a meta-analysis of widespread data available on freeridership in ARPs, identifying freeridership drivers for these programs.

Achieving a deeper understanding of the reasons why freeridership varies, and how it can be affected by changes in program design and other external factors, can aid utilities in making informed decisions about program design. Effectively designing, implementing, and evaluating energy-efficiency ARPs requires changing utilities' perceptions regarding freeridership. Rather than simply an exogenous factor outside of stakeholders' control, freeridership is a dynamic aspect of an overall program. Though utilities often recognize this dynamism in other demand-side management programs, companies frequently treat ARPs as simple turnkey programs, with little variation in these programs' designs and planning across utilities.

This paper builds on an analysis by Donald R. Dohrmann, presented at the 2007 IEPEC, which focused on freeridership variations among California ARPs, and emphasized the appropriate procedures for estimating net-to-gross ratios (NTG) under a self-report methodology. Our work uses data taken from multiple programs as well as more recent California data to determine factors driving freeridership (which Dohrmann represents as the difference of one minus the "attribution factor"). As we examine a larger set of data, our analysis allows us to identify key patterns in the degree of freeridership. We also analyze key program elements contributing to freeridership, such as a program's maturity, inclusion of primary units, unit characteristics, and geographical regions. Finally, we examine potential interactions between federally-funded programs (such as the State Energy-Efficiency Appliance Recycling Program [SEEARP], funded by the American Reinvestment and Recovery Act) and traditional utility-funded programs.

Background on NTG Estimation

Self-reported freeridership can be estimated using a variety of algorithms, depending on a given program type and the evaluator. Despite variations seen across many evaluations, appliance recycling efforts tend to use two main algorithms: an "attribution only" approach (outlined by Dohrmann in 2007); and an "attribution and part-use" approach (outlined by KEMA in 2004). The "attribution only" method has gained the widest acceptance, quickly becoming an industry standard.

Under "attribution only," the NTG ratio eliminates savings from participants who would have disposed of their units independently of the program (i.e., freeriders), but credits the program for destroying units that would otherwise would have been transferred to other users. Our analysis only uses data from participant surveys. Though some programs also collect nonparticipant data, restricting our sample only to these programs would have severely restricted our sample's size.

For program participants, refrigerators and freezers not recycled through a program follow four scenarios:

- The unit would have been be kept by the household, but not used.
- The unit would have been be kept by the household, and still used.
- The unit would have been discarded by the household using a method destroying the unit.
- The unit would have been discarded by the household using a method that transfers the unit to another person, where it would still be used.

Two of the four scenarios indicate freeridership:

- The unit would have been kept by the household, but not used.
- The unit would have been be discarded by the household using a method destroying the unit.

Under these scenarios, freeridership occurs because units would have been removed from the grid and not used or destroyed, even if they had not been recycled through the program. Consequently, the program cannot claim energy savings generated by the appliance's retirement. Below, Figure 1 outlines implementation procedures for ARPs we evaluated. Though exact calculations may differ slightly, most approaches employ similar algorithms.

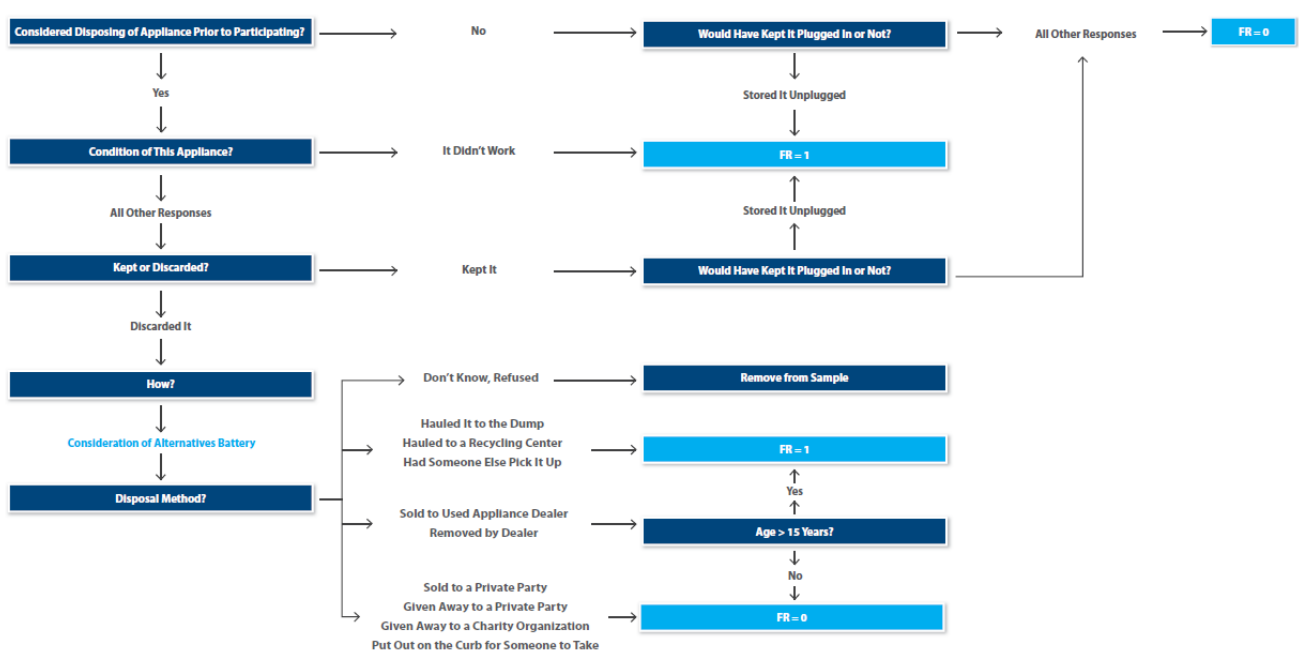

Figure 1. NTG Scoring under "Attribution Only" Method

In contrast, the "attribution and part-use" method KEMA has used incorporates the attribution schema outlined above with mean annual usage (or the part-use factor), determined from participant surveys. In this methodology, NTG serves as product of both the attribution factor (derived similarly to the method outlined above) and the part-use factor. KEMA (1998) provides a more detailed example of this methodology.

Though part-use can be important in determining savings, a question lingers as to whether it should be considered an adjustment to net savings (incorporated into the NTG) or gross savings. As this paper does not address this issue, only the attribution factor was used in analyzing studies using the "attribution and part-use" methodology.

SEEARP

Using funds from the American Recovery and Reinvestment Act, the U.S. Department of Energy set aside $300 million for energy-efficient ARPs, promoting purchases of high-efficiency, ENERGY STAR-qualified appliances through SEEARP. State energy offices administered the program, with each state required to cover 50% of program administrative costs. Rebates went to individuals, not businesses or government agencies. Most of these programs began in 2010, and virtually all of them exhausted available funds by that year's end.

In many cases, states either explicitly or implicitly attempted to coordinate SEEARP efforts with utility ARPs, raising possible attribution issues. As outlined in Goldman (2011), federal and state incentive programs can confuse participants and complicate determining savings attributable to the utility program. For example, would a customer, interested in purchasing an efficient refrigerator and referred to a utility recycling program to dispose of their old unit, be scored as a freerider under the current NTG paradigm? To address this issue, we added control variables to all programs operating during disbursement years in regions receiving SEEARP rebates.

Methodology

In estimating impacts of various program characteristics, we used a meta-analytic regression approach, collecting evaluated NTG estimates for a wide variety of programs, along with their respective uncertainties. We then used these estimates to specify a regression model that predicted estimated NTG, subject to an array of explanatorily variables related to the program and its participants. This way, we could infer potential freeridership drivers for these programs.

With data compiled for as many ARPs as possible, we reviewed evaluation reports across a number of years and regions. We identified all relevant variables we believed would have sufficient data and be available and consistent across evaluations. These included:

- Age of program[1]
- Region
- Evaluator
- Appliance type
- Incentive level
- Participant, nonparticipant, and overall NTG estimates[2]

[1] Age was calculated by taking the difference of the evaluated year and the program start year. In cases of multiyear evaluations, the mean was taken of evaluated years.

- Part-use factor
- Mean appliance age
- Mean appliance size

Table 1 (below Figure 2) lists evaluations with adequate data for inclusion. When individual reports contained estimates by appliance and/or program year (in the case of multiyear studies), each unique NTG estimate was considered a unit of analysis. For many studies, the analysis used two NTG estimates: one for refrigerators and another for freezers. In other cases, evaluation addressed only one appliance type, or a single NTG estimate was used for both appliance types.

Due to limited data availability, our final dataset could potentially exhibit bias. First, studies the Cadmus Group conducted may be overrepresented in the sample, largely due to the access we had to raw and intermediate data. Though we used the vast majority of evaluation reports found, those rejected often fell into two categories: either they provided inadequate elaborations of their NTG methodologies; or they had insufficiently reported program characteristics.

Given inconsistent use of nonparticipant NTG and a desire to limit methodological heterogeneity, NTG values estimated from participant surveys were used as the dependent variable for analysis. This approach, along with using only attribution factors for values estimated using the "attribution and part-use" method, avoided the need for study effects controls in modeling. Nonetheless, study effect tests were conducted for use of alternate NTG methodologies and for individual evaluators.

Collected input data were examined to inform the functional form of variables employed in the model. Superficial examination of relevant variables revealed most to be approximately normal.[3] In particular, given the normal distribution of the dependent variable, participant NTG, we felt an ordinary least squares regression proved most favorable; based on its ease of interpretation and relative efficiency.

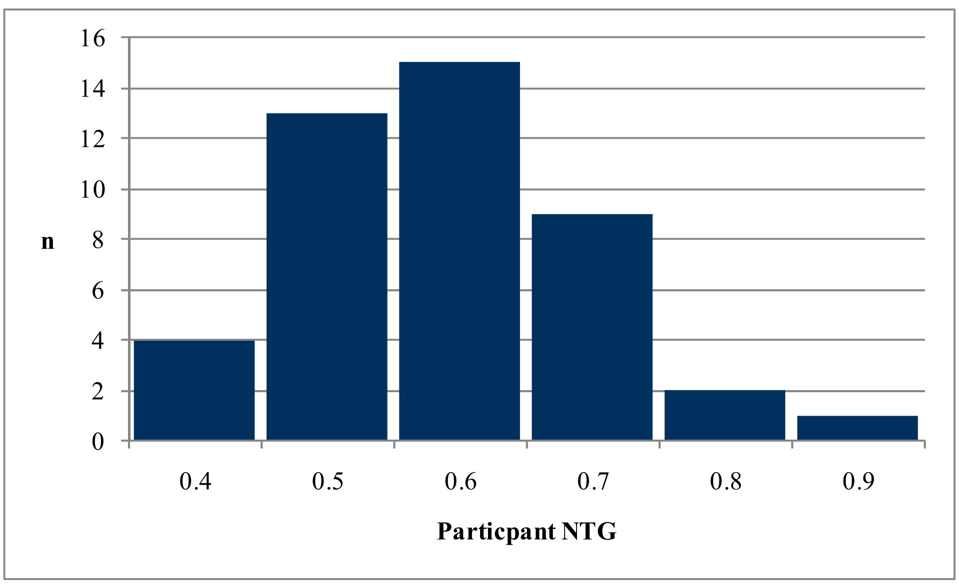

Figure 2. Sample Distribution of Participant NTG Estimates

[2] As noted, for programs using the "attribution and part-use" methodology, the attribution factor was used rather than the NTG estimate.

[3] In the final analysis, variables were found to be significantly non-normal were transformed to better approximate normality.

Table 1. Studies Considered for Analysis

Utility	State	Year	Evaluator	NTG Type 1	NTG Type 2
Ameren Illinois	IL	2009	Cadmus	Refrigerator	Freezer
Ameren Illinois	IL	2010	Cadmus	Refrigerator	Freezer
Commonwealth Edison	IL	2009	Navigant	Refrigerator	Freezer
Consumers Energy	MI	2010	Cadmus	Refrigerator/ Freezer	
CPUC (PGE)	CA	2004–2005	ADM Associates, Inc.	Refrigerator	Freezer
CPUC (PGE)	CA	2006–2008	Cadmus	Refrigerator	
CPUC (SCE)	CA	2004–2005	ADM Associates, Inc.	Refrigerator	Freezer
CPUC (SCE)	CA	2006–2008	Cadmus	Refrigerator	
CPUC (SDGE)	CA	2004–2005	ADM Associates, Inc.	Refrigerator	Freezer
CPUC (SDGE)	CA	2006–2008	Cadmus	Refrigerator	
NCPA	CA	2003	Robert Mowris & Associates	Refrigerator/ Freezer	
Northeast Utilities	CT	2004	NMR, RLW	Refrigerator	Freezer
Ontario Power Authority	ON	2007	Cadmus	Refrigerator	Freezer
Ontario Power Authority	ON	2008–2009	Cadmus	Refrigerator	Freezer
Pacificorp	ID	2006, 2007, & 2008	Cadmus	Refrigerator	Freezer
Pacificorp	UT	2006, 2007, & 2008	Cadmus	Refrigerator	Freezer
Pacificorp	WA	2006, 2007, & 2008	Cadmus	Refrigerator	Freezer
PNM	NM	2009	KEMA	Refrigerator	Freezer
Sacramento Municipal Utility District	CA	2003	Heschong Mahone Group	Refrigerator	Freezer
Sacramento Municipal Utility District	CA	2006	ADM Associates, Inc.	Refrigerator	Refrig-erator
Southern California Edison	CA	1994	Xenergy	Refrigerator	Freezer
Southern California Edison	CA	1996	Xenergy	Refrigerator	Freezer
Southern California Edison	CA	2002	KEMA-Xenergy	Refrigerator	Freezer
Snohomish PUD	WA	2006	Snohomish PUD	Refrigerator/ Freezer	
Salt River Project	AZ	2009	Cadmus	Refrigerator	Freezer
Salt River Project	AZ	2010	Cadmus	Refrigerator/ Freezer	
Progress Energy	WI	2008	PA Consulting	Refrigerator	

Meta-analysis differs from primary data analysis in that values input to a model are, in themselves, estimates. That is, each estimate of effect size—in our case, the proportion of savings attributable to the program—has its own sampling error. If we used these values without weighting, estimates with lower levels of uncertainty would be treated identically as those with higher levels. Though this would still result in asymptotically unbiased estimators (given a large enough sample size), the method can be rather inefficient. Thus, inverse variance weighting commonly is used to account for differentials in sampling error (Hunter & Schmidt, 2004).

In the past, reporting sampling error for NTG estimates has been relatively inconsistent. When we could find these in evaluation reports, they were used in weighting calculations. Where absent, variance was calculated assuming calculations used to estimate NTG were, in essence, estimators of proportion. Given the variance of a proportion estimate is only a function of that estimate and its sample size, we could calculate weights for each NTG value that, at the very least, gave greater weight to studies with larger sample sizes. Sample weights were calculated as follows:

$$weight_i = \frac{n}{s_i^2}$$

Where, if s_i is unknown:

$$s_i = \sqrt{NTG_i(1 - NTG_i)}$$

Once sample weights were calculated for each estimate, data could be modeled. Prior to data collection, the population model was hypothesized as:

$$NTG_i = \beta_0 + \beta_1 \log(incent_i) + \beta_2 \log(age_i) + \beta_3 \mathbf{prim}_i + \beta_4 \mathbf{CA}_i + \beta_5 \mathbf{SEEARP}_i$$

Where:
NTG_i = Participant NTG for evaluation i
$incent_i$ = Incentive level per appliance for evaluation i
age_i = Age of program in years for evaluation i
$prim_i$ = Proportion of appliances considered primary units for evaluation i
CA_i = Dummy variable equaling 1, if evaluation i was for a California utility, and 0 otherwise
$SEEARP_i$ = Dummy variable equaling 1, if evaluation i took place in a region and year where SEEARP rebates were distributed, and 0 otherwise

In addition to this hypothesized model, model specifications were tested using alternate functional forms of continuous variables, including squared and natural logs. Regional variables were tested in a variety of forms, serving as proxies for differences in program saturation and cultural attitudes. Appliance types were also tested to see if significant NTG differences occurred between appliance types.

Despite our confidence in the hypothesized model, we tested for study effects of the "attribution and part-use" methodology and for evaluations conducted by Cadmus to ensure comparability of NTG values was justified. Versions of this model and alternates were run with and without dummy variables, equaling one in the presence of these study effects and zero otherwise.

Results

Our final model came reasonably close to expectations. After testing the alternate hypotheses and specifications outlined above, we chose a model nearly mirroring the hypothesized model, requiring only slight adjustments (in particular, a regional dummy, specifying non-coastal regions, was found more significant than simply using one for California). As the study effect accounting for differing NTG methodologies also was found marginally significant, it was included in the model. The final model was specified as:

$$NTG_i = \beta_0 + [\beta_1 \log(incent]_i) + [\beta_2 \log(age]_i) + \beta_3 \mathbf{prim}_i + \beta_4 \mathbf{mid}_i + \beta_5 \mathbf{attPU}_i + \beta_6\ \mathbf{SEEARP}_i$$

Where:
NTG_i = Participant NTG for evaluation *i*
$incent_i$ = Incentive level per appliance for evaluation *i*
age_i = Age of program in years for evaluation *i*
$prim_i$ = Proportion of appliances considered to be primary units for evaluation *i*
mid_i = Dummy variable equaling 1, if evaluation *i* was for a utility in a non-coastal state, and 0 otherwise
$attPU_i$ = A study effect dummy variable equaling 1, if evaluation *i* used the "attribution and part-use" methodology, and 0 otherwise
$SEEARP_i$ = Dummy variable equaling 1, if evaluation *i* took place in a region and year where SEEARP rebates were being distributed, and 0 otherwise

This model's estimation was robust, with an adjusted R^2 of 0.43 and most coefficients significant at the $\alpha = 0.10$ level. Table 2 presents parameter estimates.

Table 2. Final Parameter Estimates (n= 44)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation Factor
Intercept	0.50633	0.03528	14	<0.0001	0
log(incent)	0.02326	0.01255	1.9	0.0718	1.44
log(age)	0.0508	0.02093	2.4	0.0202	2.29
prim	-0.2345	0.05196	-4.5	<0.0001	1.65
mid	0.06253	0.03633	1.7	0.0935	1.56
attPU	-0.046	0.02948	-1.6	0.1268	1.31
SEEARP	0.1089	0.07441	1.5	0.1517	1.26

Based on their theoretical merit, we included attPU and SEEARP in the model, despite slightly insignificant parameter estimates. Meta-analysis texts often stress the importance of including study effects, hence the inclusion of attPU. For the SEEARP dummy, we felt the directionality of the coefficient of interest should be retained in the model. We recognized, however, its coefficient was of less significance and should not necessarily be assigned too great a weight in interpreting the model.

The model supported arguments often made regarding ARP freeridership. That is, the model implies, holding other variables in the model constant:[4]

- Incentive level has a negative, though diminishing, impact on program freeridership. This implies price signals from program incentives. This positive impact, however, is for the log of incentive levels and, therefore, of diminishing impact.
- The program's maturity has a negative, though diminishing, impact on program freeridership, likely due to the early rush of inoperable or unused units typically recycled in a program's early years.

[4] The "attribution and part-use" methodology study effect has not been included in the model's interpretation as it was not considered of primary interest. For a further exploration of the debate over these methodologies, see Duhrmann (2007).

- Programs with greater proportions of primary refrigerators often have higher freeridership levels. Intuitively, this makes sense as these units are more likely to be disposed of and destroyed in the program's absence.
- Programs in non-coastal utilities typically have lower freeridership levels than those on the coast. This finding likely reflects a variety of cultural factors, most significantly environmental attitudes. An expanded sample, incorporating more data results from east coast utilities, would be required to interpret beyond this.
- Contrary to concerns expressed over impacts of federally-funded appliance rebate programs, this model implies the SEEARP program had a negative effect on program freeridership (though this effect does not appear strongly significant).
- Though not included in the model output, every model specification indicated relationships between appliance types and freeridership are of little to no significance.

Conclusions

Though the model we present by no means offers a complete picture of ARPs' freeridership drivers, it may serve as the beginning of a broader conversation regarding program effects. The model infers some factors driving freeridership fall outside stakeholders' control. For instance, as programs mature, they often see decreasing freeridership trends. Others factors, however, program planners may be able to control. For instance, this analysis supports the theory that programs accepting primary refrigerators experience higher freeridership levels. It also appears to indicate little significant difference in freeridership levels between refrigerators and freezers.

The most important message, however, we believe can be drawn from this study is freeridership should not be treated as a variable exogenous to program design and outreach, as sometimes happens in turnkey programs. NTG estimates often can have as great or greater impact on net savings as gross savings measurements and verification. Continuing such analysis may aid both program implementers and evaluators in better understanding ways to target non-naturally occurring segments of their given market, therefore reaping the benefits of greater net savings.

References

ADM Associates, Inc. 2007. *Measure and Verify Savings of Refrigerator Recycling Program*. Draft #3. Sacramento, CA: Sacramento Municipal Utility District.

The Cadmus Group. 2010. *Residential Retrofit High Impact Measure Evaluation Report*. San Francisco, CA: California Public Utilities Commission.

The Cadmus Group. 2011. *Consumers Energy 2010 Evaluation Activity and Summary Report*. Lansing, MI: Consumers Energy.

The Cadmus Group. 2008. *Impact and Process Evaluation of Ontario Power Authority's Great Refrigerator Roundup Program*. Ontario, Canada: Ontario Power Authority.

The Cadmus Group. 2008. *Impact and Process Evaluation of Ontario Power Authority's Great Refrigerator Roundup Program*. Ontario, Canada: Ontario Power Authority.

The Cadmus Group. 2009. *Appliance Recycling Evaluation-PY 1*. St. Louis, MO: Ameren Illinois Utilities.

The Cadmus Group. 2009. *PowerWise Appliance Recycling Program FY 2009 Evaluation*. Tempe, AZ: Salt River Project.

The Cadmus Group. 2010. *2008 and 2009 Great Refrigerator Roundup Program—Impact Evaluation*. Ontario, Canada: Ontario Power Authority.

The Cadmus Group. 2010. *Appliance Recycling Evaluation-PY 2*. St. Louis, MO: Ameren Illinois Utilities.

The Cadmus Group. 2010. *Idaho Refrigerator and Freezer Recycling Program 2006–2008*. Salt Lake City, UT: Rocky Mountain Power.

The Cadmus Group. 2010. *SRP Energy Efficiency Portfolio FY 2010 Impact Evaluation: PowerWise Appliance Recycling Program*. Tempe, AZ: Salt River Project.

The Cadmus Group. 2010. *Utah Refrigerator and Freezer Recycling Program 2006–2008*. Salt Lake City, UT: Rocky Mountain Power.

The Cadmus Group. 2010. *Washington Refrigerator and Freezer Recycling Program 2006–2008*. Portland, OR: Pacific Power.

Dohrmann, D., J. Peterson, J. Reed, S. Samiullah, and S. Westberg. 2007. "Net Savings Estimation in Appliance Recycling Programs: A Review and Empirical Analysis with Recent California Data." *In proceedings of the 2007 IEPEC Conference* .Chicago, IL: International Energy Program Evaluation Conference.

Goldmand, C. A. 2011. *Interactions between Energy Efficiency Programs funded under the Recovery Act and Utility Customer-Funded Energy Efficiency Programs*. http://escholarship.org/uc/item/9xq6s41n. Berkeley, Calif.: Lawrence Berkeley National Laboratory.

Heschong Mahone Group, Inc. 2003. *Measurement and Verification of SB5X Energy Efficiency Programs for the Sacramento Municipal Utility District*. Sacramento, CA: Sacramento Municipal Utility District.

Hunter, J. E., and F. L. Schmidt. *Methods of Meta-Analysis: Correcting Error and Bias in Research, Volume II.* Newbury Park, CA: Sage Publications.

KEMA. 2009. *Evaluation Measurement and Verification of Public Service Company of New Mexico's Electric Energy Efficiency Programs.* Albuquerque, NM: Public Service Company of New Mexico.

KEMA-Xenergy, Inc. 2004. *Measurement and Evaluation Study of 2002 Statewide Residential Appliance Recycling Program.* Rosemead, CA: Southern California Edison.

Navigant Consulting. 2010. *Evaluation Report: Residential Appliance Recycling.* Chicago, IL: Commonwealth Edison.

Nexus Market Research, Inc. 2005. *Impact, Process, and Market Study of the Connecticut Appliance Retirement Program: Overall Report.* Hartford, CT: Northeast Utilities.

PA Consulting Group. 2003. *Appliance Turn-In Program-Free Rider Analysis*. Madison, WI: Wisconsin Focus on Energy.

Robert Mowris & Associates. 2003. "*Measurement and Verification Report for NCPA SB5X Refrigerator Recycling.*" Final Report to NCPA.

Smit, K. L. 2007. *2006 Refrigerator/Freezer Program Evaluation*. Everett, WA: Snohomish Public Utility District No. 1.

Xenergy, Inc. 1996. *Impact Evaluation of 1994 Spare Refrigerator Recycling Program.* Rosemead, CA: Southern California Edison.

Xenergy, Inc. 1998. *Impact Evaluation of the Spare Refrigerator Recycling Program*. Rosemead, CA: Southern California Edison.